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INDICATORS OF TECHNICAL ANALYSIS ON THE BASIS OF MOVING AVERAGES AS PROGNOSTIC METHODS IN THE FOOD INDUSTRY

▪ *Andrea Kolkova*

Abstract

Competitiveness is an important factor in a company's ability to achieve success, and proper forecasting can be a fundamental source of competitive advantage for an enterprise. The aim of this study is to show the possibility of using technical analysis indicators in forecasting prices in the food industry in comparison with classical methods, namely exponential smoothing. In the food industry, competitiveness is also a key element of business. Competitiveness, however, requires not only a thorough historical analysis not only of but also forecasting. Forecasting methods are very complex and are often prevented from wider application to increase competitiveness. The indicators of technical analysis meet the criteria of simplicity and can therefore be a good way to increase competitiveness through proper forecasting. In this manuscript, the use of simple forecasting tools is confirmed for the period of 2009-2018. The analysis was completed using data on the main raw materials of the food industry, namely wheat food, wheat forage, malting barley, milk, apples and potatoes, for which monthly data from January 2009 to February 2018 was collected. The data file has been analyzed and modified, with an analysis of indicators based on rolling averages selected. The indicators were compared using exponential smoothing forecasting. Accuracy RMSE and MAPE criteria were selected. The results show that, while the use of indicators as a default setting is inappropriate in business economics, their accuracy is not as strong as the accuracy provided by exponential smoothing. In the following section, the models were optimized. With these optimized parameters, technical indicators seem to be an appropriate tool.

Keywords: forecasting, technical indicator, exponential smoothing, simple average moving, exponential average moving, competitiveness
JEL Classification: C53, G17, M21

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1. INTRODUCTION

Prognosis is an integral part of corporate governance. Prognostic practice is currently applied using a wide range of different approaches and methods. Forecasting methods can be classified in two ways. Qualitative methods include for example personal evaluation, panel match, the Delphi method, historical comparison, and market research. The second group consists of quantitative methods, mostly reling on trending or causal models. In this paper, certain quantitative methods will be applied, namely trend design.

The importance of using quantitative methods in business was evidenced in a research by Wisniewski (1996), with the proportion of enterprises using quantitative methods found to be 66 %. A rate of 24 % of companies indicated that the benefit of these methods is very high, while 7 % of respondents in this research claimed no benefit. At this time, most business managers in enterprises applying quantitative methods used them to establish basic and descriptive statistics, cash flow discounting, quality control and inventory. Approximately 67 % of companies used decision-making, compensation methods, with more than 50 % of such companies using simulations or regression analysis. Of course, it can be assumed that the use of quantitative methods in the corporate economy has increased even more with the development of computing. With the proliferation of this technology, the number and complexity of the methods and models used for the prognosis of business variables have also increased. We can now make prognoses-based predictions using fuzzy logic, artificial neural networks, genetic algorithms, as well as chaos theory.

The aim of this study is to show the possibility of using technical analysis indicators, a method otherwise used predominantly for stocks, currencies and other financial assets, in predicting prices in the food industry in comparison with classical methods, namely exponential smoothing. This analysis examines accuracy based on ex-post forecasting.

2. THEORETICAL BACKGROUND

The history of prognosis is relatively short, dating only from the 1960s and early 1970s. The categorization as a separate scientific discipline is not unambiguous, and even the very definition of prognosis has varied considerably since its inception.

For example, Holcr (1981) defines prognosis as a form of a forecast which meets certain requirements, and it must contain the time or space interval in which the predicted phenomenon is or will be discovered. The interval must be final, and there must be a principle possibility of an a priori estimation of the predicted phenomenon; the predicted phenomenon must be verifiable and, finally, the particular prognosis must be formulated completely accurately and unambiguously.

Gál (1999) defines prognosis as a conditional statement about the future of an object or phenomenon based on scientific knowledge.

According to Wishniewski (1996), the intention of prognosis is to reduce the uncertainty of knowledge about the future and provide additional information to allow managers to assess alternative options in the context of future conditions as well as to evaluate the future consequences of current decisions.

More modern approaches to forecasting then include the definition of the prognosis as a method of transforming past experience into the expected future.

To Vincur & Zajac, prognosis (2007, p. 12) is defined as a scientific discipline, the subject of which is the study of the technical, scientific, economic and social factors and processes that act on the development of the world's objective reality and which aims to create a vision - the prognosis of a future condition resulting from the interconnected effects of these factors and processes.

Forecasting methods can be broken down into several categories, with the most well-known and most widely used divisions being within the general categories of qualitative and quantitative methods. Miller & Swinehart (2010) categorized methods into three different groups: exploratory or normative methods, evidence-based methods, and assumptions based on evidence. The third grouping is then a classical breakdown into qualitative and quantitative methods. Moro et al. (2015) classify methods as quantitative, semi-quantitative and qualitative methods. Kesten & Armstrong (2014) divide forecasting methods into simple and complex forecasting along with a whole range of other subdivisions, as depicted in Figure 1.

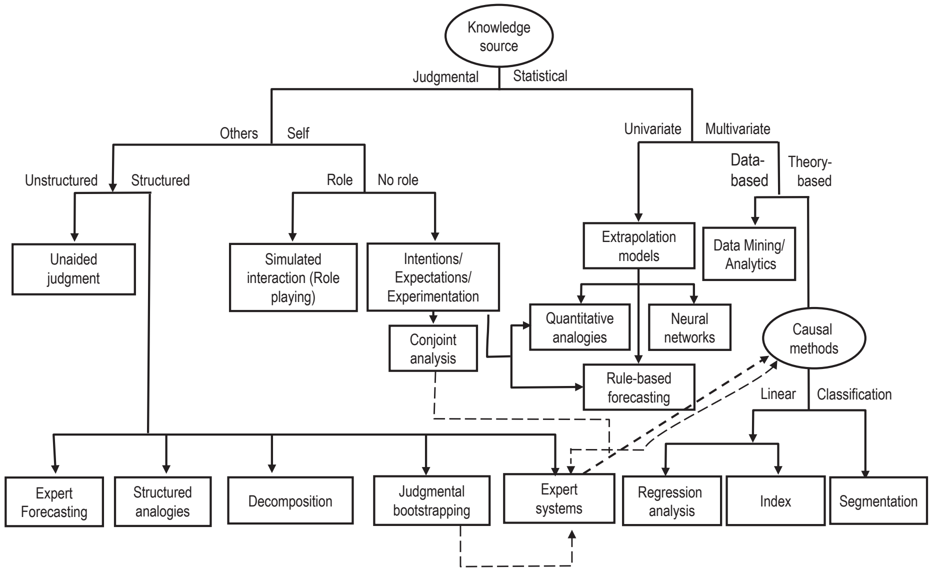

Fig. 1 – Methodology Tree of Forecasting. Source: Armstrong & Green, 2014.

In this paper, the breakdowns set forth in Esmaelian et al. (2017) on quantitative, semi-quantitative and qualitative methods will be used.

2.1 Qualitative forecasting

Qualitative methods usually do not duplicate numerical evaluations of data, but the professional appreciation and verbal evaluation of the studied variables. These methods include, for example, an expert panel where a group of experts within a given organization study and discuss a given quantity from different points of view (Wisnivski, 1996). Another method is the relevant tree (Daim et al, 2006), a way of identifying the development phases, objectives and basic elements of a given enterprise quantity. A very similar method is the futures wheel, in which the event or quantity being investigated is considered the core of a wheel, and events or variables that can affect it are considered to be vanes. A very well-known and used technique is the SWOT analysis method, by which experts identify the strengths, weaknesses, opportunities and threats of the company or product. The literature review can also be considered another search method (Moro et al, 2015).

2.2 Quantitative forecasting

These methods are usually based on mathematical-statistical techniques and numerical calculations, as indicated in Esmaelian et al. (2017). These include: trend analysis and trend extrapolation, which will be detailed in Chapter 3.1. Multi-stage analysis is a method that combines several models, as defined along with other concepts by Antonic et al. (2011).

We can also include the lesser known Future Workshop method by Martino (2003), as well as system dynamics, a method that makes predictions based on dynamic tools such as neural networks, fuzzy logic, genetic algorithms, or chaos theory.

In this paper, among the quantitative methods of forecasting, new methods of technical analysis will be included as possible tools of forecasting in the corporate economy. These will be presented along with the trend analysis and trend extrapolation method, which explained in greater detail in Chapters 3.1 and 3.2.

2.3 Semi-quantitative methods

Semi-quantitative methods include, for example, monitoring. This method uses systematic loops to identify ideal conditions by means of feedback information. Another popular method is brainstorming, a process that collects a set of ideas about the future of an individual or a group of people. Morphological analysis, questionnaire/surveys, scenario planning can also be characterized as this type of method.

The Delphi method (Esmaelian, 2017), which uses questionnaires in consecutive rounds to gather the views of as many experts as possible and to reach consensus, has also become popular. Also in wide use is stakeholder mapping (Saritas et al., 2013), (Vishnevskiy, 2015), a method which uses statistical techniques to predict who the stakeholders are, where they are and why they are interested in the product, bailout, etc. The text / data mining method used by, for example, Moro et al (2015), is one of the most recent techniques put into use.

3. RESEARCH OBJECTIVE AND METHODOLOGY

In this paper, a prognosis regarding the evolution of selected prices in the food industry will be based on historical prices and the ex-post forecast will be tested. The high prediction capability of the ex-post model is a prerequisite for using the ex-ante prognosis model. The ex-post relationship and the ex-ante prognosis are shown in Figure 2.

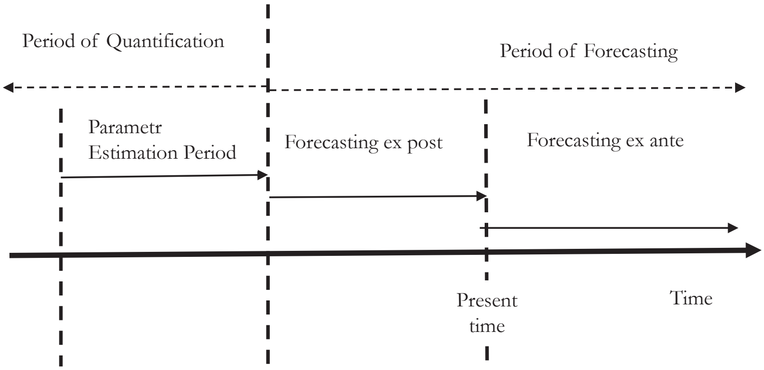

Fig. 2 – Time in Forecasting. Source: own according to Marček (2013), Vincúr (2007)

Data for the main raw materials of the food industry, namely wheat food, wheat forage, malting barley, milk, apples and potatoes, has been analyzed. The data was obtained from the Czech Statistical Office from the monthly data collections from January 2009 to February 2018 in the Czech Republic. The data file has been analyzed and modified. Missing values were found regarding milk and potatoes and replaced by linear interpolation. Descriptive statistics of the data are defined in Table 1.

Tab. 1 – Descriptive Statistic of the Analyzed Data. Source: own

	N	Min	Max	Mean		SD	Variance
	Statistic				SE	Statistic	
wheat food	110	2612	6117	4214.04	87.305	915.662	838436.090
wheat forage	110	2400	5714	3838.84	76.713	804.575	647340.560
malting barley	110	3055	6029	4641.52	65.566	687.662	472878.894
cow’s milk	110	5921	9808	7860.31	98.128	1029.174	1059199.738
potatoes	111	2159.0	7314.0	4498.469	132.0651	1391.3926	1935973.272
apples	111	6931.0	14493.0	9895.765	126.8946	1336.9180	1787349.705

The statistical programs SPSS and R (with TTR and FORECAST packages) were used for the analysis.

3.1 Forecasts based on exponential equalization

For this article, quantitative methods of forecasting based on exponential alignment were selected. Exponential smoothing is used for short-term forecasting in various modifications. Prognoses based on exponential smoothing consist of weighted averages of past values, with scales exponentially decreasing with the age of the data used (Hyndman, 2018). Exponential alignment methods include simple exponential smoothing, Holt’s exponential smoothing and Winter’s exponential smoothing.

As Bergmeir et al (2016) states, “the general idea of exponential smoothing is that recent observations are more relevant to forecasting than older observations, meaning that they should be weighted more highly.”

Simple exponential smoothing defines the prognosis as an exponential average and is used only for non-periodic time series. The relationship of the extended equation has the Shape,

$S_t = \alpha \sum_{i=0}^{t-1}(1-\alpha)^i y_{t-1} + (1-\alpha)^t S_0$, where (1)

with T being the length of the time series, y_{t-1} the value of the time series, $\alpha \in (0, 1)$ the equalization constant, and S_0 the initial equalization value

Brown's multiple exponential smoothing defines the prognosis of polynomial trends with multiple exponential averages, which are obtained by another exponential equalization of already obtained exponential averages.

Holt extended Brown's exponential smoothing by an adaptive estimation of the trend component with the new balancing constant β (Vincur & Zajac 2007). The equalization constant can be defined thusly,

$\beta = \beta(S_t - S_{t-1}) + (1-\beta)\widehat{\beta_{1,t-1}}$, where (2)

$S_t - S_{t-1} = \widehat{\beta_{0,t}} - \widehat{\beta_{0,t-1}}$ is the current state of trend and $\beta_{1,\,t-1}$ is the adaptive estimate of the trend directive over time. β is then the equalization constant. Holt's double parametric linear exponential smoothing is a modification for the stochastic trend series.

Damped trend methods have emerged as a response to the drawbacks of Holt linear methods that show a continuous trend. Empirical evidence, however, suggests that this can lead to excessive forecasts, especially in the longer forecast horizon. Methods of damped trends then include a parameter that dampens the trend on a straight line (Hyndman, 2018).

There are currently several other methods summarized by Taylor (2003) as an additive damped trend method, multiplicative damped trend method, additive Holt-Winters method, multiplicative Holt-Winters method, Holt-Winters damped method.

3.2 Forecasts based on technical analysis indicators

The objective of the technical analysis is to anticipate the future development of assets based on an analysis of their past developments. Techniques based on technical indicators are always based on mathematical statistics. The technical analysis uses not only technical indicators, but also graphical methods, with a more modern name of price action which are known even from the 18th century, when the Japanese applied their first candle charts to their rice deals. Today, they are published slightly less than technical indicators such as Lee & Jo (1999), and are the subject of research rather based on programming.

There are a lot of technical indicators. Back in 1988, Colby published an encyclopedia of technical market indicators (Colby, 2003). George Lane published his Lane's stochastic oscillator more than three decades ago (Lane, 1984), or even in the 1970s, the relative strength developed by Wilder (1978). In the 80s-90s of the 20th century, indicators belonging to a group of channel systems were published, for Bollinger bands, John Bollinger (Bollinger, 1992), or Kaufman (1987).

Of the newer indicators, for example, the Chaikin oscillator is known (Achelis, 2001) or today the most widely used MACD indicator introduced by Appel (2005). In 2007 (Cheung & Kaymak, 2007), a concept combining technical indicators and fuzzy logic was introduced. Abbasi and Abouec also used a system derived from neuro-fuzzy logic (Abbasi & Abouec, 2008). In 2009, Chavarnakul & Enke, (2009) developed a hybrid exchange trading model using the Neuro-fuzzy concept called the Genetic Algorithm (NF-GA). In 2015, technical indicators (specifically MACD and the lesser-known Gann-Hilo indicator) and fuzzy logic were used again (Chourmouziadis & Chatzoglou, 2015). Currently, there are still new indicators based on both fuzzy modeling and a combination of individual statistical and mathematical indicators, and so the list of indicators is far from complete. The existing ones are then subjected to various tests (da Costa, 2015; Kolkova, 2017; Kresta, 2015).

In this study, an innovative attempt is made to apply technical indicators to business economy phenomena as well. Technical analysis indicators have not yet been used to predict the business economy and are not yet part of any research work, so their use can be a tool to significantly increase the competitiveness of the business. For the sake of scale, only some technical indicators have been selected, namely indicators on the basis of rolling averages, which are also one of the most used in the practice of financial transactions. Since the exponential equalization method is also based on the methodological basis of moving averages, it can be assumed that these indicators may also be an appropriate tool for predicting business phenomena.

Sliding averages calculate the average value of the data in the width of its timeframe. For example, a 7-day moving average means the average value of the last week, 14 days in the last two weeks. After joining the rolling average of all days, we create a rolling average curve.

The moving average is now a whole range. The basis is Simple Moving Average (SMA) and can be defined by the relationship,

$$SMA = \frac{\sum_1^N input}{n}, \text{ where} \qquad (3)$$

N is the number of days for which the SMA is numbered. Moving averages are used to smooth the data in an array to help eliminate noise and identify trends. The simple moving average is literally the simplest form of a moving average. Each output value is the average of the previous n values. In a simple moving average, each value in the time period carries equal weight, and values outside of the time period are not included in the average. This makes it less responsive to recent changes in the data, which can be useful for filtering out those changes.

Exponential moving average (EMA) is considered to be a better tool than a simple moving average (Elder, 2006) because it attaches greater weight to current data and changes in price correspond faster than with the simple one. It is used in countless technical indicators. It can be expressed by the relationship,

$$EMA = EMA_{-1} + K \cdot (input - EMA_{-1}), \text{ or} \qquad (4)$$

$$EMA = K \cdot input + (1 - K) \cdot EMA_{-1}, \text{ where} \qquad (5)$$

$$K = \frac{2}{N+1}, \text{ where} \qquad (6)$$

N is the number of days to quantify the EMA.

Double exponential moving average (hereafter DEMA), as reported by FM Labs (2016), is a smoothing indicator less lag than straight EMA. It is more complex than just moving average. DEMA was developed by Mulloy (1994). It can be defined by the relationship,

$$DEMA = 2 \cdot EMA(input) - EMA(EMA(input)) \tag{7}$$

The Zero-Lag exponential moving average is a variation of the EMA. This indicator was created by Ehlers & Way (2010) and keeps the benefit of the heavier weighting of recent values but attempts to remove lag by subtracting older data to minimize the cumulative effect. It is expressed by the relationship,

$$ZLEMA = K \cdot \left(2 \cdot input_0 - input_{-lag}\right) + (1 - K) \cdot ZLEMA_{-1}, \text{ where} \tag{8}$$

$$lag = \frac{n-1}{2}. \tag{9}$$

Hull moving average (hereafter only HMA), developed by Alan Hull (2012), is an improved variant of the moving average, which shows the moment of trend reversal quite accurately. It is defined by the relationship,

$$HMA_t = \frac{1}{\sum_{i=1}^{s} i} \cdot \sum_{i=0}^{s-1} (s - i)(diff_{t-i}), \text{ where} \tag{10}$$

$$m = \left\lfloor \frac{n}{2} \right\rfloor, \tag{11}$$

$$s = \left\lfloor \sqrt{n} \right\rfloor, \tag{12}$$

$$first_t = \frac{1}{\sum_{i=1}^{s} i} \cdot \sum_{i=0}^{m-1} (m - i)(input_{t-i}), \tag{13}$$

$$second_t = \frac{1}{\sum_{i=1}^{s} i} \cdot \sum_{i=0}^{n-1} (n - i)(input_{t-i}), \tag{14}$$

$$diff_t = 2 \cdot first_t - second_t, \text{ or} \tag{15}$$

$$HMA = WMA(2 \cdot WMA\frac{n}{2} - WMA(n), sqrt(n)), \text{ where} \tag{16}$$

WMA is weighted moving average.

Arnaud Legoux moving average (hereafter ALMA) by the authors Legoux & Kouzis-Loukas uses the curve of the normal (Gauss) distribution which can be placed by offset parameter from 0 to 1. This parameter allows regulating the smoothness and high sensitivity of the moving average. Sigma is another parameter that is responsible for the shape of the curve coefficients. This moving average reduces a lag of the information but still being smooth to reduce noises.

$$ALMA = \frac{1}{NORM} \sum_{i=1}^{size} p(i) e^{-\frac{(i-offset)^2}{\sigma^2}}, \text{ where} \tag{17}$$

size is the window size.

3.3 Forecasting accuracy

If it is possible to predict the values by multiple methods or models, it is advisable to choose the one that provides the smallest errors. The error rate should be evaluated at the time of known values in the ex-post forecasting period. For the evaluation then, if the chosen error estimating variable is 0 then the prognosis is flawless. In the case of a positive error, the model underestimates the fact, and vice versa, in the case of a negative model error, the fact overestimates the fact. R-squared, root mean square error (hereafter RMSE), mean absolute percentage error (hereafter MAPE), maximum absolute perceived error (hereafter MaxAPE), mean absolute error (hereafter MAE), maximum absolute error (hereafter MaxAE) and the normalized Bayesian information criterion (hereafter Normalized BIC) are used as prognostic accuracy measures. The formulas in this article were drawn mainly from (Vincur & Zajac, 2007) and (Marček, 2013). R-squared is usually called the coefficient of determination. It is the proportion of variation in variable explained by the model,

$$R^2 = \frac{\sum_{p=1}^{N}\left(y_p - \widehat{y_p}\right)^2}{\sum_{p=1}^{N}\left(y_p - \bar{y}\right)^2}, \text{ or} \qquad (18)$$

$$R^2 = 1 - \frac{\sum_{p=1}^{N} {e_p}^2}{\sum_{p=1}^{N}\left(y_p - \bar{y}\right)^2}. \qquad (19)$$

R-squared statistics, however, are generally considered to have relatively poor predictive abilities. Armstrong (2001, p. 461) identified 6 studies on the use of R-Squared and found a relatively small relationship with the precision forecast. Therefore, other statistics are introduced, which are simpler, more useful, but also easier to understand than R-squared (Hyndman & Koehler, 2006). Newer methods are discussed in Chen et al (2017).

When defining the RMSE variable, it is necessary to first describe the Mean square error (MSE), which expresses an average square error by the relationship,

$$MSE = \frac{1}{M}\sum_{p=n+1}^{N}\left(y_p - \widehat{y_p}\right)^2. \qquad (20)$$

However, it is preferable to use the standard deviation, which is RMSE by the relationship,

$$RMSE = \sqrt{MSE}. \qquad (21)$$

MSE and RMSE have the same unit as the original time series. In the same units, the MAE is also declared, this being the average deviation of the actual values from the forecasts. It can be described by the relationship,

$$MAE = \frac{1}{M}\sum_{p=n+1}^{N}\left|y_p - \widehat{y_p}\right|. \qquad (22)$$

Other indicators are referred to as relative forecast accuracy rates and are expressed as a percentage. These indicators do not depend on the time series units of measure, and therefore we can use them when comparing the forecast accuracy of different variables. One of these is, for example, MAPE, which represents an average error of forecasts compared to actual values by the relationship,

$$MAPE = \frac{1}{M}\sum_{p=n+1}^{N}\frac{\left|y_p - \widehat{y_p}\right|^2}{y_p}. \qquad (23)$$

The MaxAPE value is also expressed as a percentage and represents the largest predicted error. On this basis, we can get an idea of the worst possible scenario of our forecast.

Max AE is then the largest forecasted error, expressed in the same units as the dependent series. Like MaxAPE, it is useful for imagining the worst-case scenario of your forecasts. Maximum absolute error and maximum absolute percentage error may occur at different series points, for example when the absolute error for a large series value is slightly larger than the absolute error for a small series value. In that case, the maximum absolute error will occur at the larger series value and the maximum absolute percentage error will occur at the smaller series value.

Normalized Bayesian Information Criterion (hereafter Normalized BIC) can be defined, a general measure of the overall fit of a model that attempts to account for model complexity. It is a score based upon the mean square error and includes a penalty for the number of parameters in the model and the length of the series. The penalty removes the advantage of models with more parameters, making the statistics easy to compare across different models for the same series.

4. RESULTS AND DISCUSSION

As for using technical indicators in the basic settings, which are most commonly used in technical analysis on financial markets (and the use of 20 daily averages in particular), the results are summarized in Table 2.

Tab. 2 – Results of Exponential Smoothing and Technical Analysis Indicator's with Basic Parameters. Source: own

Model	Accuracy	Exponencial Smoothing				Technical Analysis Indicator's					
		Simple	Brown	Damped	Holt	EMA 20	SMA 20	DEMA	ZLEMA 20	HMA	ALMA
wheat food	RMSE	199.895	184.920	168.200	184.336	1014.806	1076.107	930.002	926.719	923.905	673.857
	MAPE	2.650	2.576	2.236	2.570	18.686	20.304	19.727	15.970	17.865	11.521
fodder forage	RMSE	168.149	151.884	139.042	151.921	978.389	1027.367	896.482	896.482	510.335	572.448
	MAPE	2.666	2.567	2.233	2.546	19.066	19.314	19.035	19.035	9.118	11.069
malting barley	RMSE	154.781	160.256	152.075	155.494	836.348	907.382	735.855	671.347	584.276	354.960
	MAPE	2.489	2.669	2.466	2.578	13.942	14.907	14.554	11.137	9.757	5.746
cow's milk	RMSE	174.132	97.551	95.181	98.021	1427.000	1351.769	1866.379	1812.204	1821.136	692.846
	MAPE	1.809	0.931	0.906	0.931	15.455	14.510	21.439	18.980	19.473	7.802
potatoes	RMSE	696.916	750.428	702.429	700.028	1542.526	1158.997	1237.669	2246.876	2259.597	1497.130
	MAPE	8.875	10.927	8.798	8.872	24.644	17.473	22.180	35.900	36.536	27.839
apples	RMSE	855.858	949.074	863.816	860.431	1638.171	1689.903	1949.888	1685.321	1709.477	1340.735
	MAPE	5.726	6.561	5.730	5.739	10.360	10.412	13.157	11.669	12.438	10.932

The results clearly indicate that the technical analysis indicators do not achieve precision scores as do the exponential smoothing predictive models, which would lead to the hypothesis that these are not a suitable tool for predicting business phenomena. The most appropriate pricing tools in the food industry are highlighted in Table 2. For both types of wheat, barley and milk, it is clearly best to use the so-called damped trend method according to both criteria. For potatoes based on the accuracy measured by RMSE, simple exponential smoothing is the most suitable, and according to MAPE, again the damped trend. Apples measured by RMSE showed the best prediction ability for Holt models and MAPE simple exponential smoothing.

Therefore, it is also appropriate to focus on finding appropriate parameters of individual technical indicators for this prediction. The optimization parameter has been chosen for the number of periods included in moving averages. The search for the most suitable parameters was implemented again using the R program with forecast package (Hyndman, 2008) and RKWard (Rödiger et al., 2012), based on the programming capabilities of this language using the FOR function. Overall, for each of the five indicators, 50 predictive models were analyzed for each commodity within food industry. Overall, 1,500 models were analyzed, with only those with the best RMSE or MAPE results evaluated. Models based on the HMA indicator were not included in the calculation due to the calculation methodology, in which the number indicator is not the key element.

The calculation was carried out using the R program with the following syntax (example of the milk product):

```
library(TTR)
library(forecast)
milk<-(my.data[,”milk”])
for (i in 1:50)
{accuracy(ema<-EMA(milk, i),
milk[(i+1):105,1])}
```

Table 3 includes the best test results compared to basic 20-day average models. The table shows that optimized results clearly deliver better results than non-optimized models.

Tab. 3 – Results of the Optimized Models. Source: own

Technical Analysis Indicator’s											
Model	Accuracy	EMA		SMA		DEMA		ZLEMA		ALMA	
		original parameters	optimized parameters	original parameters	optimized parameters	original parameters	optimized parameters	original parameters	optimized parameters	original parameters	optimized parameters
wheat food	RMSE	1014.806	592.844	1076.107	667.145	930.002	680.575	926.719	554.743	673.857	359.728
	MAPE	18.686	14.302	20.304	15.699	19.727	14.093	15.970	13.936	11.521	5.260
fodder forage	RMSE	978.389	781.706	1027.367	382.809	896.482	706.507	896.482	776.745	572.448	354.475
	MAPE	19.066	14.227	19.314	10.405	19.035	13.103	19.035	14.835	11.069	9.662
malting barley	RMSE	836.348	110.695	907.382	119.761	735.855	377.093	671.347	136.841	354.960	201.444
	MAPE	13.942	2.197	14.907	2.239	14.554	6.628	11.137	2.647	5.746	3.221
cow’s milk	RMSE	1427.000	737.117	1351.769	659.397	1866.379	238.274	1812.204	582.670	692.846	343.246
	MAPE	15.455	7.800	14.510	6.582	21.439	2.169	18.980	6.453	7.802	3.663
potatoes	RMSE	1542.526	534.376	1158.997	446.514	1237.669	465.184	2246.876	905.592	1497.130	843.751
	MAPE	24.644	9.646	17.473	8.056	22.180	9.528	35.900	18.935	27.839	13.477
apples	RMSE	1638.171	1474.030	1689.903	1489.668	1949.888	1476.277	1685.321	1512.278	1340.735	1474.030
	MAPE	10.360	9.223	10.412	9.862	13.157	9.575	11.669	9.576	10.932	9.223

Figure 3 shows how for the milk product the technical indicators correspond to the actual evolution of the quantity. The solid line shows actual development, with the dashed lines showing the prediction.

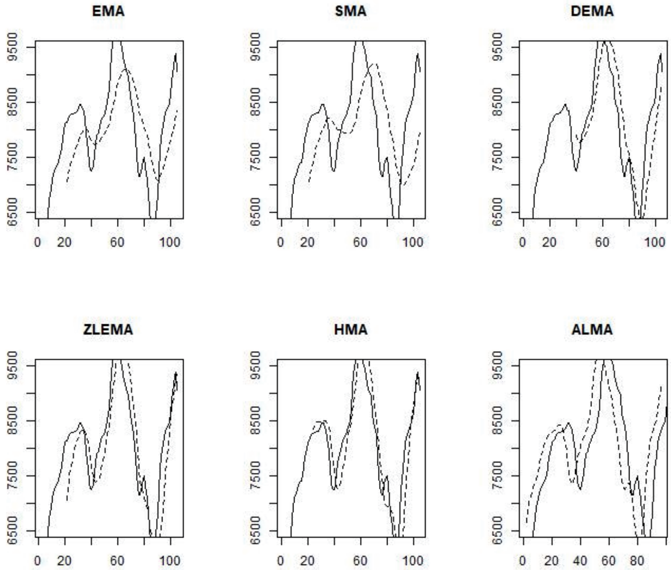

Fig. 3 – Results of Forecasting Milk on Technical Indicators Base. Source: own

Parameters of the individual models, which are best suited for the given commodity or the degree of accuracy, are presented in Table 4. The computational procedure of the optimized parameters was performed according to the syntax in the R language mentioned previously.

Tab. 4 – Optimized Period of Technical Indicators. Source: own

Model	Accuracy	EMA	SMA	DEMA	ZLEMA	ALMA
		optimized parameters				
wheat food	RMSE	50	50	35	50	6
	MAPE	6	12	9	17	6
fodder forage	RMSE	50	45	50	50	50
	MAPE	50	45	50	50	50
malting barley	RMSE	49	49	11	49	6
	MAPE	49	49	10	49	6
cow's milk	RMSE	37	45	49	44	6
	MAPE	37	45	49	45	6
potatoes	RMSE	49	49	33	49	6
	MAPE	43	43	32	49	6
apples	RMSE	6	7	11	10	6
	MAPE	12	10	11	36	12

Comparing the accuracy of optimized technical indicators and exponential equalization, we can no longer say that technical indicators are a totally inappropriate tool (see Table 5). Most commodities are still better predictable through exponential smoothing, but with malting barley the highest RMSE and MAPE model is based on the EMA technical indicator. For potatoes, the SMA model is the best model based on RMSE.

Tab. 5 – Accuracy of the best Optimized Models. Source: own

Model	Accuracy	Exponencial Smoothing				Technical Analysis Indicator's				
		Simple	Brown	Damped	Holt	EMA	SMA	DEMA	ZLEMA	ALMA
wheat food	RMSE	199.895	184.920	168.200	184.336	592.844	667.145	680.575	554.743	359.728
	MAPE	2.650	2.576	2.236	2.570	14.302	15.699	14.093	13.936	5.260
wheat forage	RMSE	168.149	151.884	139.042	151.921	781.706	382.809	706.507	776.745	354.475
	MAPE	2.666	2.567	2.233	2.546	14.227	10.405	13.103	14.835	9.662
malting barley	RMSE	154.781	160.256	152.075	155.494	110.695	119.761	377.093	136.841	201.444
	MAPE	2.489	2.669	2.466	2.578	2.197	2.239	6.628	2.647	3.221
cow's milk	RMSE	174.132	97.551	95.181	98.021	737.117	659.397	238.274	582.670	343.246
	MAPE	1.809	0.931	0.906	0.931	7.800	6.582	2.169	6.453	3.663
potatoes	RMSE	696.916	750.428	702.429	700.028	534.376	446.514	465.184	905.592	843.751
	MAPE	8.875	10.927	8.798	8.872	9.646	8.056	9.528	18.935	13.477
apples	RMSE	855.858	949.074	863.816	860.431	1474.030	1489.668	1476.277	1512.278	1474.030
	MAPE	5.726	6.561	5.730	5.739	9.223	9.862	9.575	9.576	9.223

Figure 4 shows the forecasting of malting barley and potatoes. The graph shows ex-post forecasting in which the full line represents actual historical development of the commodity and the broken line predicts results based on the models of technical indicators for EMA malting barley and SMA potatoes.

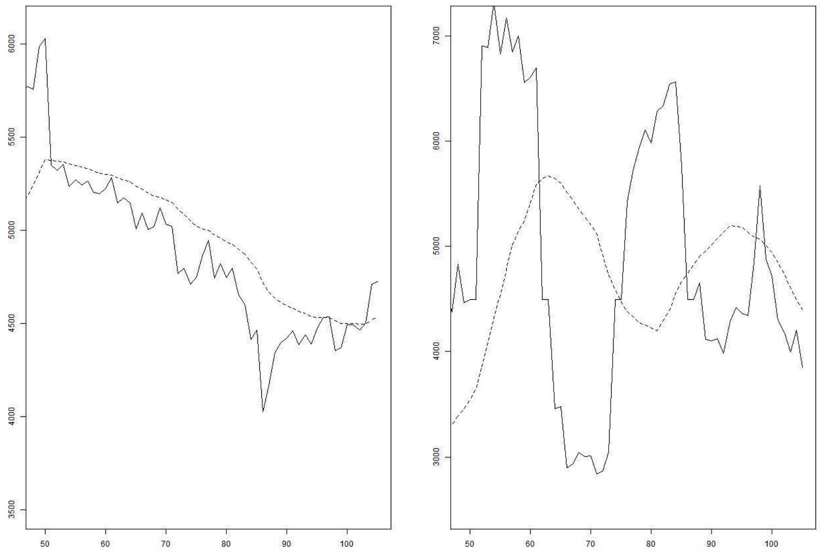

Fig. 4 – Forecasting malting barley and potatoes on the technical indicator base. Source: own

Most prices in the food industry, mainly wheat food, wheat forage, cow's milk, are still best suited to predict results using exponential smoothing, namely the damped trend. The use of simple exponential smoothing is best to predict the price of apples. However, other results are no longer precluded technical analysis. In malting barley, the Exponential Moving Average appears to be the most unpredictable variable. As for potatoes, the results are ambiguous and the RMSE accuracy is the smallest SMA, but MAPE should choose damped exponential smoothing. Figure 5 expresses the forecast not only ex-post but also ex-ante for 30 periods.

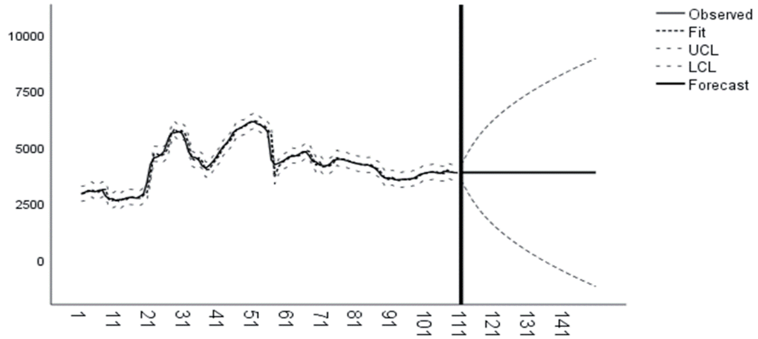

Fig. 5 – Forecasting Wheat food with Damped trend. Source: own

Finally, Table 6 shows the parameters of forecasting on the exponential smoothing damped trend for Wheat Food, for which the most damped trend is based on the analysis in this article.

Tab. 6 – Parameters of the forecasting Wheat Food by the Damped trend. Source: own

Exponential Smoothing Model Parameters						
Model			Estimate	SE	t	Sig.
Wheat food-Model_ Dameped trend	No Trans-formation	Alpha (Level)	1.000	0.273	3.660	0.000
		Gamma (Trend)	1.000	1.061	0.943	0.348
		Phi (Trend damping factor)	0.596	0.228	2.615	0.010

5. CONCLUSION

The aim of this paper was to show the possibility of using technical analysis indicators, otherwise used predominantly for stocks, currencies and other financial assets, in the prediction of prices in the food industry in comparison with classical methods, namely exponential smoothing. In this article, the effectiveness of even these simple prediction tools is confirmed, namely in a short period of time on the monthly data of prices of basic agricultural commodities. The SMA, EMA, DEMA, HMA, ZLEMA, and ALMA benchmarking indicators have been selected for the technical analysis. These are the most commonly used indicators in the financial market practice (especially for EMA and SMA). The indicators were compared with exponential smoothing predictions, and the accuracy RMSE and MAPE criteria were selected. The results show that the use of indicators in the default setting, the mostly traded with by traders, is inappropriate in business economics, and the accuracy does not match the accuracy given by exponential smoothing. In the next part, the period number parameter was optimized in technical indicators. Based on this optimization, other sliding averages were defined for all selected raw materials in the food industry. With these optimized parameters, technical indicators seem to be an appropriate tool, especially EMA and SMA, which are the most common tools for predicting financial markets. EMA is a suitable tool to predict malting barley and SMA for potatoes when the accuracy is measured using RMSE. For other raw materials, it is preferable to use classical tools, especially the dumped trend for wheat food and wheat forage cow's milk and potatoes with MAPE accuracy. For apples, it is preferable to use simple exponential smoothing. However, in order to ensure a higher competitiveness of enterprises, it is necessary to use the models in practice. In the academic sphere, the idea of the simplicity of prognostic models for use in practice is described by Zellner (2001) in his KISS concept ("keep it sophisticatedly simple") as well as by Green & Armstrong (2015), who confirm this theory in scientific work. The reason is the relative complexity of the models, which lose their effectivity for use in decision making by managers. Research by Soyer & Hogarth (2012) has even shown that more complex static models are often difficult to be understood even for academics. Crone, Hibon & Nikolopoulos (2011) compared the comparatively simple exponential smoothing methods used in this article to neural network methods, with the results indicating that the typical neural network forecast was 4% less accurate than the naive model prognosis.

The methodology of the indicators of technical analysis definitely corresponds with the principles of simplicity and can thus be beneficial to improving the competitiveness of businesses. The fairly simple principles that traders apply to securities and their derivatives can also be used in the corporate economy and in predicting their quantities. Further research may focus on other indicators of technical analysis such as channel systems. Verification could also be performed for different business sectors. Here the result would be to determine where the industry can use the predictions based on technical indicators to increase the competitiveness of a particular business.

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Contact information

Ing. Andrea Kolkova, Ph.D.
VSB - Technical University of Ostrava
Faculty of Economy
Department of Business Administration
Czech Republic
E-mail: andrea.kolkova@vsb.cz
ORCID: 0000-0002-4764-3164