

# Dynamics of Exchange Rates and Oil Price: Adaptive Analysis and Forecasting

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## ABSTRACT

Multivariate generalizations of the modified and adaptive time series correlation coefficients are obtained using the example of the dependence of currency pairs quotations and Brent crude oil price. The analysis of the movement of exchange rates and oil price in the R software environment. A much more detailed data analysis than the classical theory suggestion is obtained. Based on the identified trends in the dynamics of these markets, short-term forecasting was carried out using ARIMA, TBATS models and neural networks.

**Keywords:** forecasting, currency quotations, oil price, modified and adaptive correlation coefficients, ARIMA, TBATS, neural networks

## 1. INTRODUCTION

Currency trading is a popular investment and trading market strategy. Investors and traders playing the world currency market buy highly profitable currencies with the aim of investing in securities for profit. Manage the risk, while making decisions. Cope with it or suffer losses missing the opportunities. A necessary condition for the risk management effectiveness is the accuracy of forecasting the exchange rate dynamics.

Currency risk arises from open or incompletely hedged positions in a specific currency. The volatility of foreign currency can destroy the profitability of expensive interstate investments. At the same time it can put a company in unfavorable competitive conditions relative to foreign partners. It can also lead to high transaction costs and restrain investment because of the uncertainty. One of the main causes of currency risk is an imperfect analysis of the correlation in the movement of quotations of currency pairs and prices of energy commodities.

Technical analysis of time series is based on the data of mass behavior of factors of the foreign exchange and energy markets. It is possible to carry out short-term and medium-term forecasting by picking out the trends in the dynamics of these markets.

studied series can be considered locally stationary by the Barnett - Ayson criterion, the periods of this stationarity are rather short compared with the duration of non-stationary segments [2]. So, for example, for the USD/RUB currency pair, the stationary segment amounted to 14.89% of the entire series. It implies the inapplicability of classical forecasting models.

The methodological basis of this study is adaptive forecasting [3–4].

In [5] showed that the accuracy of forecasts for time series obtained on the basis of an econometric model with exogenous real data is worse than that for adaptive models. The essence of this approach is to adjust the initial estimate of the base model parameters in time based on the new data obtained at each next step. The model is adapting to new, constantly changing conditions.

### 1.2. Purpose and subject of the study

The subject of the study is the global currency market represented by non-stationary time series of currency quotations and the oil price.

The purpose of the study is to identify and track development trends, structural changes in the economy under the influence of the financial market.

### 1.1. Methodological base

In [1] the financial series were studied for global and local stationarity. Analysis dynamics of direct quotations of currency pairs (USD/RUB, USD/EUR, USD/CAD, USD/GBP) showed no global stationarity of the corresponding time series. The series was defined as locally stationary at the segment, when the distribution function of the random components of the analyzed time series in this segment was unchanged. Although the

## 2. METHODS AND MATERIALS

As a statistical base of the study, the data on the exchange rates of six currencies against the US dollar (USD) is used: Russian Ruble (RUB), Euro (EUR), Canadian Dollar (CAD), British Pound Sterling (GBP), Chinese Yuan (CNY), Japanese Yen (JPY) and oil price per barrel.

The length of each time series is assumed to be 7,306 daily observations for the period from January 1, 2000 to January 1, 2020.

The time series is written as  $x_{1t}, x_{2t}, \dots, x_{it}$  where  $t$  is the time instant of the investigated segment of the series.

## 2.1. Analysis of financial time series using a modified correlation coefficient

The modified correlation coefficient gives an idea of the averaged correlation properties of two non-stationary series. It makes it possible to judge whether there is a positive or negative correlation at time instant  $t$  by the coincidence or mismatch of the growth signs of the variables of interest.

$$r_{mod} = \frac{\sum_{t=2}^T \Delta x_{1t} \Delta x_{2t} \dots \Delta x_{it}}{\sum_{t=2}^T |\Delta x_{1t} \Delta x_{2t} \dots \Delta x_{it}|}, \quad (1)$$

where  $\Delta x_{it} = x_{it} - x_{it-1}$ .

The correlation coefficient calculated for each moment or period of time based on the accumulated results of increments of time series is a function of time. I.e. it is a time series that can be used to analyze the correlation in time of the considered phenomena.

The chart (Figure 1) shows the modified correlation coefficient of exchange rates and oil price calculated in a recurrent manner.

## 2.2. Analysis of financial time series using an adaptive coefficient and its comparison with a modified correlation coefficient

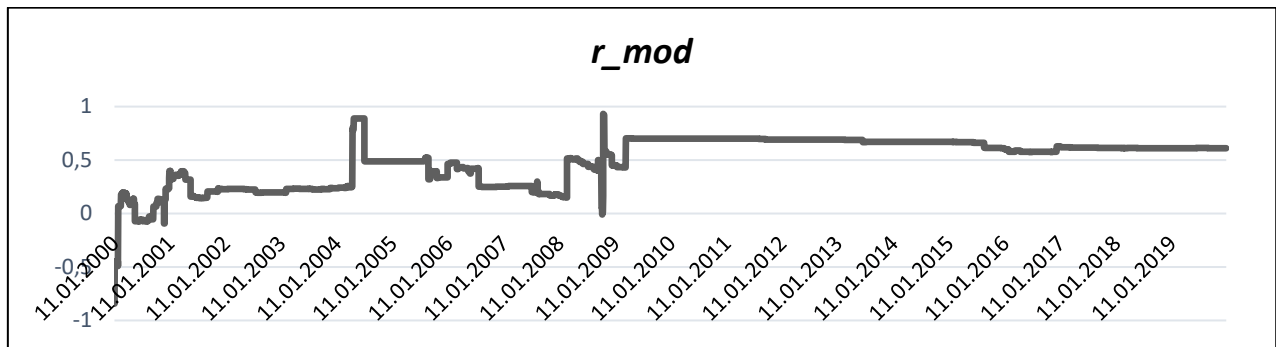


Figure 1. Chart of the modified correlation coefficient of currency pairs and oil price

The adaptive correlation coefficient makes it possible to identify the dynamics of the relationship between non-stationary time series, which can become weaker or stronger. In this case, the hypothesis of the constancy of the correlation relationship used in (1) will have to be recognized as invalid. Arithmetic averaging over time gives only a very rough result telling nothing about the movement of the correlation coefficient in time. Therefore, another recurrent correlation coefficient is proposed.

$$r_t(\alpha) = \frac{s_t}{d_t}, \quad (2)$$

where  $s_t = (1 - \alpha)s_{t-1} + \alpha(\Delta x_{1t} \Delta x_{2t} \dots \Delta x_{it}), t = 1, 2, \dots, T$ .

$$d_t = (1 - \alpha)d_{t-1} + \alpha|\Delta x_{1t} \Delta x_{2t} \dots \Delta x_{it}|, 0 < \alpha < 1.$$

$s_t$  and  $d_t$  are exponentially weighted moving averages of the products of increments and absolute products of increments of the two series.

$\alpha$  is the smoothing constant or the adaptation parameter. It can be selected from the specified range  $[0,1]$  based on the specific application of the calculated correlation coefficient.

$d_t$  acts as a normalizing coefficient. Thanks to it  $r_t$  cannot go beyond  $-1 \leq r_t(\alpha) \leq 1$ .

The chart  $r_t(\alpha)$  relative to time shows how the correlation strength changes in the sample period.

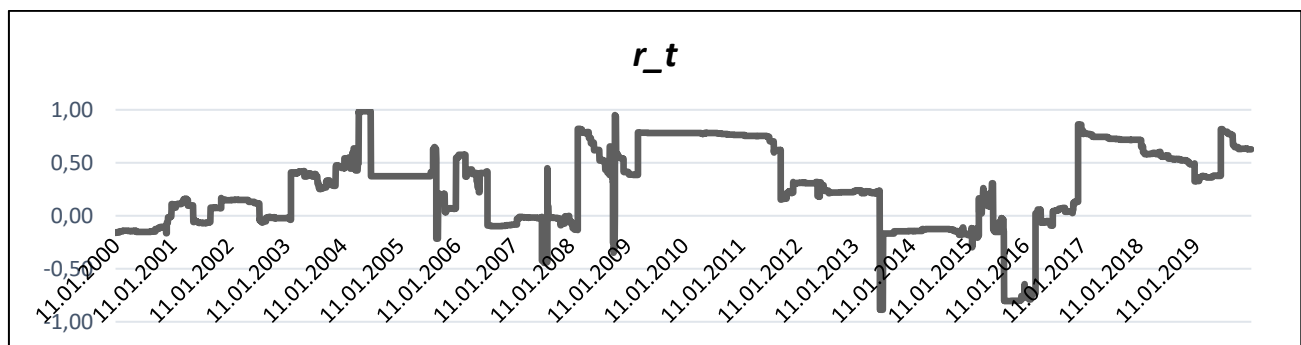
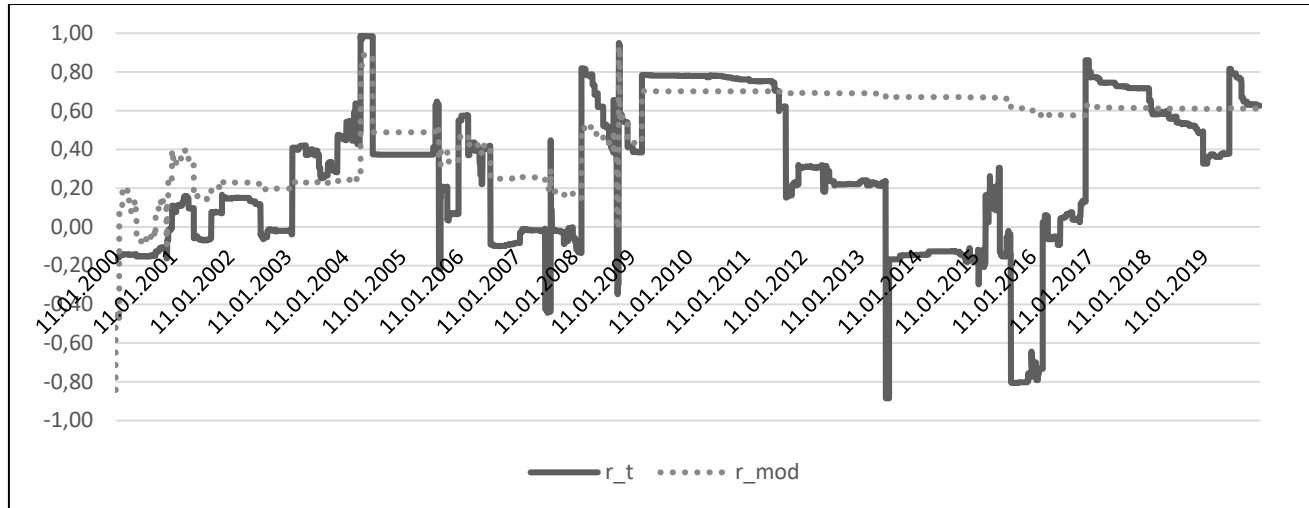


Figure 2. Chart of adaptive coefficient of correlation of exchange rates and oil price

$s_0$  and  $d_0$  are initial values defined as simple arithmetic means of the products and the absolute values of the products of increments calculated on the basis of  $T_0$  of the

earliest observations of the sample,  $0 < T_0 \leq T - 1$ . Then  $r_0 = \frac{s_0}{d_0}$  will be the initial correlation coefficient.

The chart (Figure 2) shows the adaptive correlation coefficient of exchange rates and oil price.



**Figure 3** Comparison of modified and adaptive time series correlation coefficients

In the chart of the adaptive coefficient, the same periods can be distinguished as in the case with the modified correlation coefficient. However, the adaptive coefficient is more sensitive, which is especially noticeable in the last selected period.

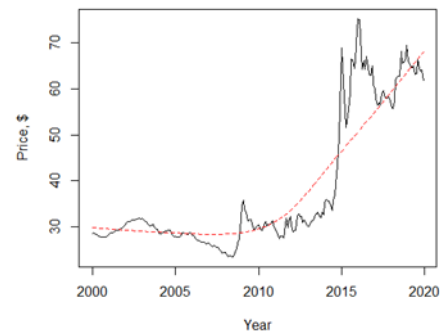
Events such as refugee crises in Europe, terrorist attacks, a collapse in the Chinese stock market are reflected here.

A comparison of the charts of the modified and adaptive correlation coefficients is shown in Figure 3.

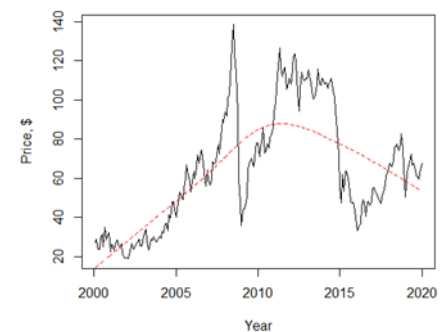
### 2.3. Analysis of the movement of exchange rates and oil price in the R software environment

To analyze the movement of exchange rates, we used quotations of USD/RUB currency pairs and Brent USD/BBL oil price. The data was taken from 1/1/2000 to 1/1/2020.

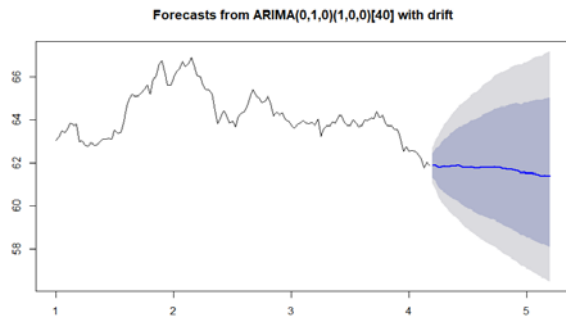
Financial and economic data taken from Quandl library [6]. To plot the corresponding charts (Figures 3.1 - 3.2), the plot function was used. To exclude the influence of noise in the series analysis, it was smoothed using the lowess function (weighted local regression).



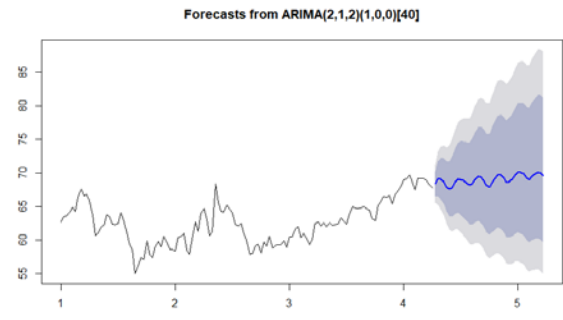
**Figure 3.1.** Time series of the USD/RUB currency pair



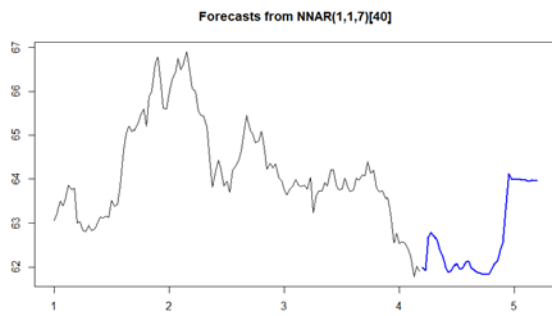
**Figure 3.2.** Time series of oil price USD/BBL



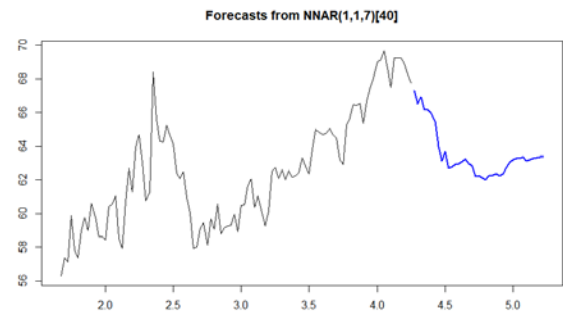
**Figure 4.1.** Data prediction using the ARIMA model of the USD/RUB currency pair



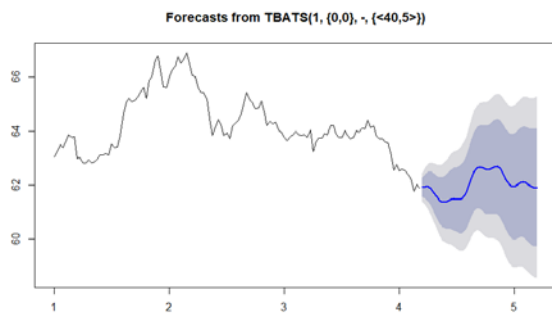
**Figure 4.2.** Data prediction using the ARIMA model of the oil price USD/BBL



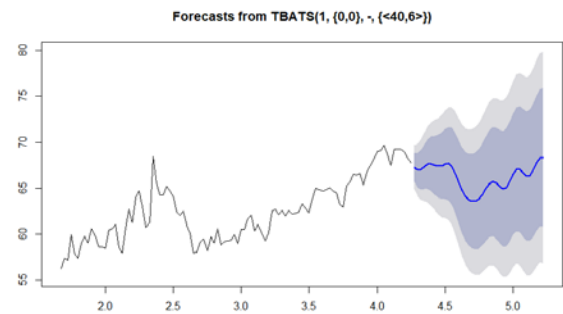
**Figure 5.1.** Data prediction using the neural network model of the USD/RUB currency pair



**Figure 5.2.** Data prediction using the neural network model of the oil price USD/BBL



**Figure 6.1.** Data prediction using the TBATS model of the USD/RUB currency pair



**Figure 6.2.** Data predicting using the TBATS model of the oil price USD/BBL

### 3. RESULTS

- I. Analysis of the charts (Figures 1-3) made it possible to identify six time periods reflecting significant structural changes in the world in the first half of 2000. The modified correlation coefficient  $r_{\text{mod}}$  shows a weak positive relationship. The beginning of the period reflects the consequences of the Asian financial crisis of 1997-1999. It arose as a result of the rapid growth of East Asian countries that received significant capital inflows. They accounted for about half of the world GDP growth. Therefore, when the rate of national currencies, stock

- indices fell in East Asian regions, inflation increased significantly affecting the production of the world product. The Asian financial crisis caused such consequences as the default in Russia in August 1998. The period also reflects the rapid growth of the economies of developing countries. Their contribution to world economic growth began to exceed the contribution of developed countries.
- II. The second half of 2000. At the beginning of the period, a weak negative relationship is observed, changing to a positive one by the end of the period. From 1999 to 2001, the United States produced about half of all global additional demand, but this result was achieved by creating an economic bubble. A bubble is characterized by a deviation of prices,

for example, stocks or assets, from their fundamental values (value of all future earnings from a stock or asset). This bubble dubbed the “dotcom” bubble burst in 2000. In the same period, OPEC countries, as well as Norway, Russia, Mexico and Oman, agreed on a general reduction in oil production. During this period, developing countries with fast-growing economies continued to play an active role in global financial markets due to globalization and the rapid spread of achievements of scientific and technological progress.

III. 2001 - 2004. The coefficient  $r_{\text{mod}}$  shows the average positive relationship. The beginning of the period reflects the Argentinean economic crisis, which led to the largest default of 132 billion US dollars. The September 11, 2001 attacks were reflected here in European stock markets quotations plummeting. Due to the sale of shares of American companies and the transfer of assets to oil, oil price rose. Nevertheless, a gradual recovery in world GDP growth began and reached its maximum during this period in 2004. The growth trend is typical for all countries, however, the United States were the locomotive of economic growth accounting for about half of the world product. Its main driving forces are high innovative activity and competitiveness, an increase in consumer spending by the population, housing construction, and investment efficiency. The development of the Japanese economy is closely related to the state of the American economy; its active recovery began. High economic growth rates were observed in the countries of East and South Asia. The high growth rate of the Russian economy also contributed to the global economy. The share of Russia in the world economy was gradually increasing. Russia's average annual economic growth rate was 6.8% versus 2.7% for the United States, 1.8% for Japan, and second only to China with 9.4%. At the same time, the problems of a huge amount of public debt and deflation remained. Economic growth in this period was due to investment activity in major industries and a slowdown in import growth. The second US campaign in Iraq, unrest in Venezuela and Nigeria led to a decrease in oil production and export from these countries and caused a sharp demand from consumers and a price leap. The main role in increasing world oil production in the Europe and Eurasia region during this period belonged to the countries of the former USSR, primarily Russia. It provided almost half of the increase in oil production. OPEC established a price range and supported it during 2000-2003 by periodically adjusting oil production quotas for its members. However, in 2004, the price of the OPEC basket went beyond the upper limit of the target price range.

IV. 2004 - 2008. The correlation coefficient  $r_{\text{mod}}$  was positive, but the relationship was gradually weakening. The beginning of the period can be described as a period of extremely high world oil

price. The reasons for this situation were high world economy growth rates, in particular, the economies of the USA and China, and the low level of free oil production capacities, which did not allow a quick increase in production to meet the growing oil demand. The sharp decline in the coefficient in 2005 may be due to the consequences of Hurricane Katrina. It resulted in oil price rising and US dollar temporarily weakening in the global currency market. In the fourth period of the study, the stage of active inflation of economic bubbles began. In 2007, the US mortgage crisis began causing a significant blow to the global real estate market and the financial market as a whole.

V. 2008 - 2009. The collapse of the economy, which began in 2008, was associated with the inflation of bubbles in the fourth period of the study and the mortgage and stock crisis in the United States. At the beginning of the period, the maximum oil price was reached, followed by a sharp decline. Its main reason was a decrease in US consumption because of the mortgage crisis. World inflation rates rose to record levels in Russia. Stock quotations of Russian companies collapsed. The crisis led to a total decline in production. The most significant industries in most countries have been affected by the recession. For many years, the world has seen a decline in oil price.

VI. 2009 - 2019. We observe a strong stable relationship between world currencies and oil price. The world economy has not fully recovered from the effects of the 2008-2009 crisis. Since 2010, the world economy has been on the way to recovery.

2020 was marked by the entry of the world economy into the global crisis triggered by the coronavirus. The result is a sharp drop in demand for oil and petroleum products. The drop is 20% only in China despite the fact that this country provided 2/3 of world oil demand. A sharp drop in prices is catalyzed by the failure to reach an agreement between Russia and OPEC. According to Minister of Energy A. Novak, the difficultly predicted uncertainties, the so-called “black swans”, are associated with the geopolitical situation.

#### 4. RESULTS AND DISCUSSION

To predict the time series, we used ARIMA (Figures 4.1 - 4.2), TBATS (Figures 5.1 - 5.2) models and neural networks (Figures 6.1- 6.2).

The ARIMA model combines two most widely used approaches to forecasting time series: autoregression - the value of the series is linearly dependent on previous values; and moving average - information on the entire history of the series is concentrated in the model errors in previous periods.

After training, a neural network is able to predict the future value of a sequence of exchange rates based on previous values, thanks to a new experimental predicting function “nnetar”. It implements the ability of a neural network to

generalize and find hidden relationships between input and output data [7].

The TBATS model makes it possible to simulate a gradually changing seasonality by introducing combinations of Fourier series into the model using the Box-Cox transformations.

In [8] showed that for a long-term forecasting period it is better to use a neural network model, while for a short-term period, the difference in forecast between the considered models is insignificant.

The time series from 7/1/2019 to 1/1/2020 was the basis for building models, while the forecast was made from 1/1/2020. The ARIMA model predicts small abrupt deviations and a stable exchange rate, since a constant process level is observed throughout the forecasting section of the currency pair. In the model of neural networks, two periods can be distinguished: the first is a sharp drop in oil price and a leap in the exchange rate, and the second is the series stabilization. It is also worth considering that forecasting is influenced by many factors that cannot be taken into account, for example, political ones. It can be assumed that neural networks predicted a crisis related to the oil price collapse, which led to an increase in the exchange rate. The forecast built using the TBATS model is similar to the forecast of neural networks. Leaps in time series are also observed here.

When comparing short-term forecasts made by three different models, one can reveal a general trend - a sharp increase in the ruble exchange rate and a drop in oil price. It is clearly seen from the predicted data that ruble is extremely dependent on oil price. This is due to the fact that the bulk of Russia's exports is oil. The economy of our country remains resource-based, in spite of spells about the need to get off the oil curse.

## 5. CONCLUSION

The modified and adaptive time series correlation coefficients are calculated using the example of the dependence of currency pair quotations and Brent crude oil price. The analysis of the movement of exchange rates and oil price in the R software environment. Using an unconventional correlation analysis of six currencies against the US dollar (USD): Russian Ruble (RUB), Euro (EUR), Canadian Dollar (CAD), British Pound Sterling (GBP), Chinese Yuan (CNY), Japanese Yen (JPY) and oil price per barrel show the relationship between the studied series and high sensitivity to change in the studied

variables. Short-term forecasts in the R environment were built using the ARIMA, TBATS and neural network models.

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