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FORECASTING CURRENCY INFLATION FOR INFLATION RISK ANALYSIS OF FINANCIAL INVESTMENT

Abstract. The need for improving methods of financial investment analysis in order to reduce risks leads researchers to exploit the modern scientific advancements especially in IT domain. Financial analytics require the ability to model and forecast future value of investigated financial parameters like currency inflation. In this paper, we analyzed the monthly inflation rate of Kazakhstan currency, using historical data from 1995 to 2020 by applying wide spread statistical and machine learning methods. The results show that the proposed research approach generates a solid forecasting accuracy and can be proposed to be included into financial investment analysis methods that could reduce inflation risk.

Keywords: time series, machine learning, neural networks, inflation, financial indicators, investment projects, investment analysis.

Introduction. Fundamentally in practice, investment analysts in order to evaluate investment projects use the net present value (hereinafter NPV) as the main financial indicator.[1] Also, for ease of calculating NPV, majority of analysts often omit an important element such as a currency inflation indicator or use it as a constant value.

$$NPV = \sum_{t=0}^{n} \frac{CF_t}{(1+N_{ir})^t} \tag{1}$$

Where CF_t is cash flow, N_{ir} is a discount rate that is usually used as nominal interest rate.[2] Since the real interest rate parameter is very difficult to predict as inflation rate varies over a monthly period depending on the economic situation of a considering country. However, financial modeling with the constant rate might deliver ineffective financial predictions especially in countries with weak economies. Nevertheless, a fairly large amount of historical data is being collected around the world and available for analysis on the public domain, including currency inflation data. Which in turn might contribute to the study and analysis of data using modern computer modeling and machine learning methods. There is an equation that considers link between inflation rate and interest rates [3]:

$$R_{ir} = \frac{1+N_{ir}}{1+I_r} - 1 \tag{2}$$

Where $R_{ir}$is real interest rate, $N_{ir}$is nominal interest rate and $I_r$is Inflation rate.The goal of this work is to forecast the inflation rate of the given equation to consider inflation risk. As inflation rate changes over a monthly time period it is recommended to apply a time series analysis method. Time series analysis is a statistical technique that deals with time series data or trend analysis. We shall examine 3 main broadly used methods to analyze and forecast inflation rate: Holt-Winter's method, SARIMA and Neural networks. Holt-Winter's smoothing method is widely applied for predicting time series that consist of seasonality and changing tendencies. [4] Holt-Winter's method uses additive and multiplicative functions to forecast.[5] SARIMAX is extended version of ARIMA that stands for Autoregressive Integrated Moving Average model, which is a well known forecasting time series model.[6] ARIMA with seasonal component that is more powerful than ARIMA is called SARIMA.[7] SARIMA is also used in many different areas for forecasting heat demand[8], production industry [9], power market prices[10] and etc. Artificial Neural Network (ANN) inspired by the brain neural network and was used to forecast time series in general[11],[12] and forecast financial data in specific[13]. ANN is considered as an alternative to statistical forecasting modeling. ANN consists of at least three layers of nodes: input, hidden and output. Except for the input nodes, each node is a neuron that uses a non-linear activation function. ANN uses a supervised learning method that divides input data into training and testing sets. The root mean-square error (RMSE)[14] is used to assess the accuracy of forecast and to compare the results of 3 forecasting models.

Methodology. Inflation indicators are considered mainly as an annual indicator, but calculations are made for each month of the year. Since inflation indicators in Kazakhstan can only be obtained for 25 years, this annual interval is a very poor indicator for data analysis. In this regard, it was decided to analyze monthly inflation rates for time series that gave us 300 records of inflation data[15]. In order to use the ARIMA model following non seasonal values of p, d and q must be correctly set. Akaike's Information Criterion (AIC) is mainly used to identify the parameters of an ARIMA model.

$$AIC(p) = nln\left(\frac{RSS}{n}\right) + 2K \tag{2}$$

Where RSS is the residual sums of squares and n is the number of data points. The model with the minimum AIC value will be chosen as the best forecasting model.[7] For supervised learning with ANN data from April 1995 to May 2015 was used as the training set, while data from May 2015 to May 2020 was used as the testing set.

In order to analyze and forecast time series data the following algorithm was proposed and used in Python programming language:

1. Load and prepare a dataset
   a. import data
   b. visualize data
2. Check data for stationarity
   a. Dick-Fuller test check[16]
   b. Checking for seasonality / trend / cycles by decomposing data [17]
3. Divide dataset into training and testing sets
4. Using library for time series analysis methods
   a. Set SARIMAX parameters and run a model:
   i. S: Seasonality. It is necessary to set up four seasonal elements affecting the time series.
   ii. AR: Autoregressive. A model that uses a dependent relationship between an observation and a number of lagging observations.
   iii. I: Integrated. Using differentiation of raw observations (for example, subtracting an observation from an observation at a previous time step) to make the time series stationary.
   iv. MA: Moving Average. A model that uses the relationship between observation and residual error from a moving average model applied to lagging observations.
   v. Set parameters and fit data to model[18]
   b. Set Holt-Winters' parameters and run a model:
   i. Check for additive and multiplicative trend and seasonal parameters
   ii. Set parameters and fit data to a model
   c. Set ANN parameters and run a model
   i. Import tensorflow.keras library

ii. Choose model and layer for ANN
iii. Set ANN parameters and fit data to model
4. Evaluate models
a. Evaluation metric selection: root mean square error (RMSE) and mean square error (MSE)
b. Model validation

Results. In this section the results of the algorithm will be provided.

Step 1. The very first step is to prepare, load t and visualize the dataset it as shown in Figure 1

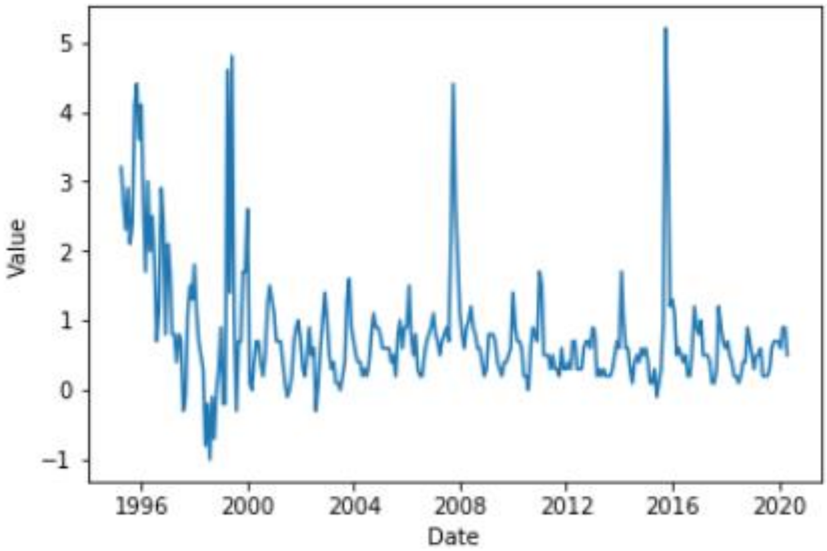

Figure 1. Dataset visualization

Step 2. After loading the data, the second significant step is to check time series for stationarity in order to use ARIMA models [11]. Results of Dickey-Fuller Test show that time series are stationary as p-value is lower than significance level of 0.05 and the Test statistic is lower than any of the critical values as shown in Table 1.

Table 1. **Results of Dickey-Fuller Test:**

Test Statistic	-4.681174
p-value	0.000091
#Lags Used	11.000000
Number of Observations Used	290.000000
Critical Value (1%)	-3.453102
Critical Value (5%)	-2.871559
Critical Value (10%)	-2.572108
dtype:	float64

Step 3.a. In this step, the dataset is divided into training and testing sets and ARIMA parameters are automatically set by searching with a minimum AIC for the training set shows following parameters: SARIMAX(2,0,0)x(0,1,1,12).

Table 2. **Results of diagnostics for SARIMAX(2,0,0)x(0,1,1,12)**

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.5372	0.043	12.498	0.000	0.453	0.621
ar.L2	0.1881	0.035	5.381	0.000	0.120	0.257
ma.S.L12	-0.8171	0.076	-10.817	0.000	-0.965	-0.669
sigma2	0.6153	0.046	13.328	0.000	0.525	0.706

According to results of diagnostics for SARIMAX parameters in Table 2 for all P>|z| show less than 0.05, thus proving that model is statistically significant.

Step 4.a. By applying most efficient parameters according to the AIC model, MSE and RMSE were 0.107 and 0.326 respectively. Results of comparing the predictions and testing dataset values is given on Figure 2.

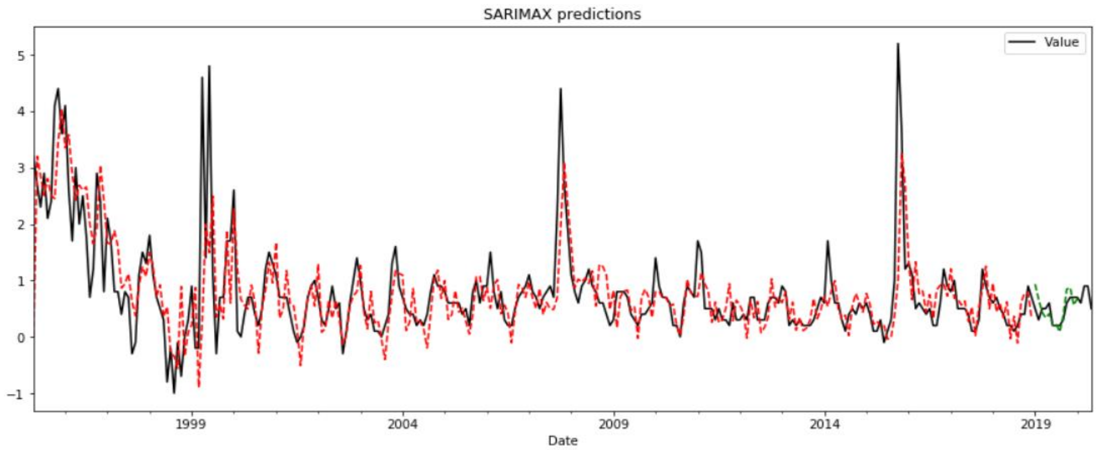

Figure 2. SARIMAX predictions on dataset

Step 3.b. By setting additive value to seasonal and trend parameters and setting seasonal period to 12, we configured the forecasting model. Holt-Winter's predictions are illustrated in Figure 3.

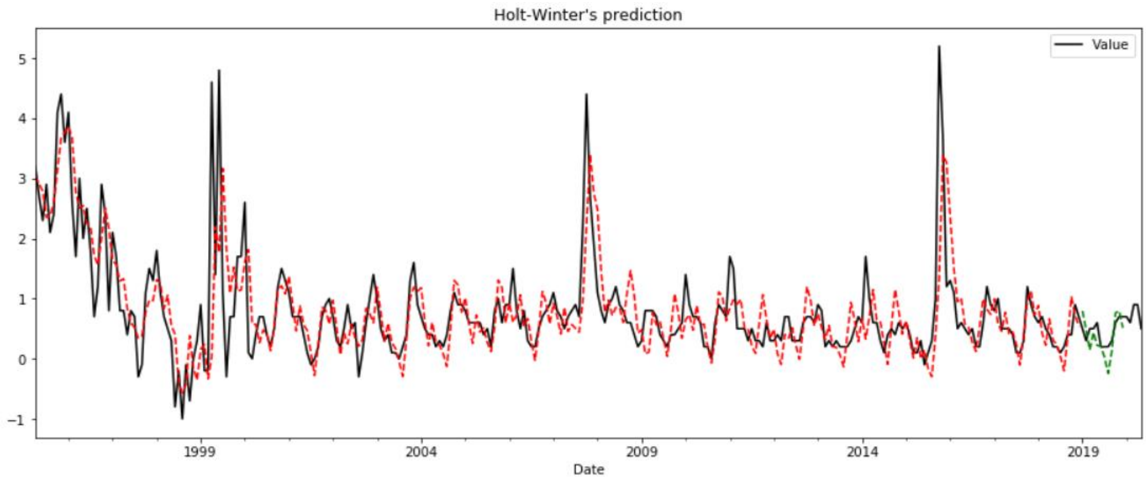

Figure 3. Holt-Winter's prediction on dataset

Step 4.b. Results for the test set of MSE and RMSE values of Holt-Winter's were 0.117 and 0.343. respectively

Step 3.c. Sequential model and Dense layer were used for the ANN forecasting model. ANN predictions are illustrated in Figure 4.

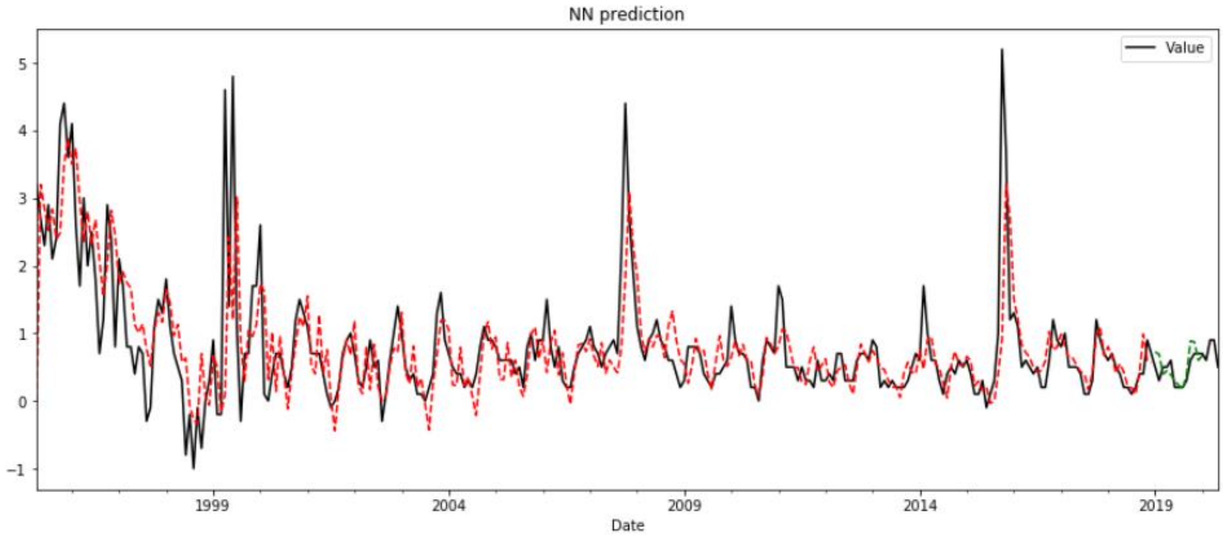

Figure 4. NN prediction on dataset

Step 4.c. Results for the test set of MSE and RMSE values of the Neural Network model were 0.092 and 0.303. respectively

Conclusion. As can be seen all 3 models showed good forecasting abilities of monthly currency inflation. RMSE of Holt-Winter's and SARIMAX models delivered very close results with slightly better results of the SARIMAX model. On the other hand, the Neural Network model showed best results on RMSE, but did not show significant progress than statistical models. All 3 models can be applied to forecast monthly inflation time series. These models can help analysts to assess real values and analyze more precisely of investment projects by assessing inflation risk. For future studies, we will be considering two main factors of improving forecasting models. First factor is the length of time series that was quite short and the second factor is the impact of pandemic that's making some changes to economics of all the countries around the world, which leads to the newest data to be included for future improvement of forecasting accuracy. Neural networks can adjust its working model parameters with forthcoming data, whereas statistical methods of time series might need remodeling the whole structure as they severely depend on new data.

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ҚАРЖЫ ИНВЕСТИЦИЯЛАРЫНЫҢ ИНФЛЯЦИЯЛЫҚ ТӘУЕКЕЛДЕРІН ТАЛДАУ ҮШІН ВАЛЮТАЛЫҚ ИНФЛЯЦИЯНЫ БОЛЖАУ

Аңдатпа. Тәуекелдерді азайту мақсатында қаржылық инвестицияларды талдау әдістерін жетілдіру қажеттілігі зерттеушілерді заманауи ғылыми жетістіктерді, әсіресе IT саласында, қолдануға итермелейді. Қаржылық аналитика валюта инфляциясы сияқты қызығушылықтың қаржылық параметрлерінің болашақ құнын модельдеу және болжау мүмкіндігін талап етеді. Бұл мақалада кең таралған статистикалық және машиналық оқыту әдістерін қолдана отырып, 1995 жылдан бастап 2020 жылға дейінгі тарихи деректерді пайдалана отырып, қазақстандық валютаның ай сайынғы инфляция деңгейіне талдау жасаймыз. Нәтижелер көрсеткендей, ұсынылған зерттеу әдісі болжамдардың жақсы дәлдігін қамтамасыз етеді және инфляция қаупін азайтуға мүмкіндік беретін қаржылық инвестицияларды талдау әдістеріне енгізу үшін ұсынылуы мүмкін.

Негізгі сөздер: уақыт тізбегі, машиналық оқыту, нейрондық желілер, инфляция, қаржылық көрсеткіштер, инвестициялық жобалар, инвестицияларды талдау.

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ПРОГНОЗ ВАЛЮТНОЙ ИНФЛЯЦИИ ДЛЯ АНАЛИЗА ИНФЛЯЦИОННЫХ РИСКОВ ФИНАНСОВЫХ ИНВЕСТИЦИЙ

Аннотация. Необходимость совершенствования методов анализа финансовых вложений с целью снижения рисков побуждает исследователей использовать современные научные достижения особенно в области IT. Финансовая аналитика требует способности моделировать и прогнозировать будущую стоимость исследуемых финансовых параметров, таких как валютная инфляция. В этой статье мы анализируем ежемесячный уровень инфляции казахстанской валюты, используя исторические данные с 1995 по 2020 годы, применяя широко распространенные статистические методы и методы машинного обучения. Результаты показывают, что предлагаемый исследовательский подход обеспечивает хорошую точность прогнозов и может быть предложен для включения в методы анализа финансовых вложений, которые могут снизить риск инфляции.

Ключевые слова: временные ряды, машинное обучение, нейронные сети, инфляция, финансовые показатели, инвестиционные проекты, инвестиционный анализ.

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