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KEYWORD RESEARCH-BASED STOCK MARKET OIL PRICE FORECAST VALIDITY TEST WITH NEURAL NETWORK

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Abstract
Stock market and global economic processes are often based on speculation, and in certain oligopoly markets, decisions are preceded by the prediction of the expected decisions of other players, i.e. we can also speak of speculative operation. In today's fast-paced world, the online press has a great influence on opinion formation through expert articles and analyses. In this article, we examine the extent to which Wall Street Journal articles influence or can influence investor inclination. In other words, the future price change can be predicted from the analysis of the articles, or more precisely, how effectively it can be predicted.

1 Introduction

In the field of economics, events that fall outside the bounds of normal expectations and thus deemed unpredictable are referred to as tail events (Nordhaus, 2011). Predicting the time-varying probability of a given variable exceeding a fixed expected maximum value is crucial in various business applications. Economic research has traditionally focused on forecasting economic indicators to anticipate potential problems, capitalize on opportunities, maintain economic stability, and reduce volatility. BVAR and FAVAR models have been utilized by many to forecast economic indicators, with varying degrees of success, particularly in the case of developing or robust economies. (Madhou et al., 2019; Langcake and Robinson, 2017) The continuos development of increasingly complex models has allowed for the analysis of more variables as a result of the possibilities provided by Big Data management, yielding faster and more efficient results. (Gupta and Kabundi, 2011)

Given that economic events are often influenced by government policies, political events, and corporate decisions, the goal is to create comprehensive forecasts if possible. For example, central banks rely on accurate predictions of inflation rates to make sound monetary policy decisions that can prevent overheating of the economy. Similarly, predicting the probability of the exchange rate falling below a certain threshold can indicate probable currency strenghtening and encourage decision-makers to adopt appropriate decisions (Kumar et al., 2003).

In financial markets, predicting that the return of a financial asset will exceed a certain pre-defined level is critical in assessing terminal risks, predicting periods of turbulence, and understanding changes in investor behavior or investment strategies.

A comprehensive analysis of the literature reveals that significant research has been conducted to predict economic factors such as oil and gas prices and interest rates, as well as their directional trends. Among the most effective and prominent forecasting methods are neural networks (Moshiri, 2000; Thakur et al., 2015; Onimode et al., 2015; Mahdiani and Khamehchi, 2016), structural models and time series (Moshiri, 2000), the conditional least squares (CLS) method (Dadgar et al., 2006), the Bayesian vector autoregressive (BVAR) methods (Heidari and Parvin, 2009), dynamic

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artificial neural networks (Naderi et al., 2018), the genetic algorithm (Fan et al., 2008), the wavelet principle with hybrid neural network (Aloui and Jammazi, 2012), and autoregressive models (Onimode et al., 2015).

Upon examining the existing literature, it becomes evident that forecasting methods can be classified into two primary categories: econometrics and artificial intelligence techniques.

In efficient markets, investors constantly update their decisions based on new information and adjust their asset positions accordingly. However, the impact of new information on asset prices depends on the type of information. Fama and French (1993, 1996, 1997) found that certain information affects all stocks and their returns, while other information is more firm-specific, impacting the returns of only certain stocks or funds. (Daniel and Titman, 1997) Moreover, investor sentiment can be influenced by non-economic factors such as weather. For instance, Kamstra et al. (2003) discovered that market returns tend to be lower in autumn and winter when the weather is gloomy, reflecting a specific behavioral disturbance associated with reduced daylight hours.

There is no consensus on what types of information affect asset prices, but investors seeking excess returns react to all information and may react differently to the same set of information. DeLong et al. (1990) in a seminal study posits that investor sentiment, defined as a belief about a company's future cash flows and risk level that is not supported by current facts, can persist for a long time, leading to asset prices that differ significantly from their intrinsic value. As a result, asset prices can be higher due to investor overreaction or lower due to investor underreaction. (Barberis et al., 1998) Thus, investor sentiment is considered one of the main drivers of observed asset pricing irregularities.

Swaminathan (1996) and Neal and Wheatley (1998) discuss closed-end fund discounts as examples of investor sentiment. Neal and Wheatley (1998) further state that net mutual fund redemptions can predict the extent of mispricing. Baker and Wurgler (2007) provide a comprehensive list of tests of investor sentiment, including among others proxies such as aggregate forecasts, changes in consumer confidence, changes in trading volume, and insider trading.

The use of Artificial Neural Networks (ANNs) in economic process forecasting has gained popularity recently. For instance, Tkacz (2001) predicted Canada's GDP with a relatively small percentage of errors using several variables, Alaminos et al. (2020) used a Neural Network to predict the inflation rate, and Galeshchuk and Demazeau (2017) used a Convolutional Neural Network for the future values of the Hungarian forint’s exchange rate. However, in the latter case, the unpredictability of government decisions significantly influenced the development of the exchange rate, making prediction challenging . As such, ANNs' methodology for analyzing texts, drawing conclusions, and forecasting economic processes continue to develop and provide more accurate predictions. (Subecz, 2019)

The objective of this study is to assess the value of articles published in online trade magazines that cover the stock market and the economy in the context of specific commodity exchange products. Specifically, we investigate the relationship between news articles published in these trade magazines and the changes in crude oil prices, with the aim of predicting future prices.

2 Method

In conducting this research, the process can be divided into three main parts. The first part involved building a database through the creation of a scraper. To ensure the reliability and relevance of the data, it was necessary to consider specific criteria such as covering a sufficiently long period, sourcing from a leading periodical with significant weight in economic life, and having a well-structured database that can be scraped. After examining several trade journals (Bloomberg, Yahoo! finance, Forbes, NYTimes, CNBC, Reuters, etc.), the Wall Street Journal was found to be the best choice. The research period covered 21 years between 2000 and 2020, and 330,435 complete articles were collected over 67 days of continuous operation.

The second part involved analyzing the collected articles using quantitative analysis. Articles that dealt with the evolution of the oil price, depending on certain indicators, were "colored" and further examined.

The third part of the research involved searching for correlations between the words used in the "colored" articles and the changes in oil prices using a neural network. The data set was divided into a training dataset comprising fo 70% of the data and a test dataset using the remaining 30% of the data. This classic approach to neural network operation was used to identify patterns and relationships between the analyzed data.

2.1 Wall Street Journal Keyword Method

In the initial round of analysis, we individually examined all 330,435 articles collected and used a set of indicator words to determine their relevance. These words were

OPEC,
WTI,
CRUDE OIL,
OIL PRICE.

Articles were considered relevant if they contained at least one of these words. We later expanded this criterion to include articles with up to 20 occurrences of these words. Out of all the collected articles, only 1.82% contained at least one of these words, resulting in a total of 6,014 articles being examined in depth.

Based on our analysis, we found that on average, there was almost one article per day containing these indicator words, with a higher frequency during major events. Therefore, we concluded that there were enough articles and links available to continue our research.

It is worth noting that the indicator words were carefully selected based on their significance in the context of our research topic, which was predicting the oil price based on articles in trade magazines.

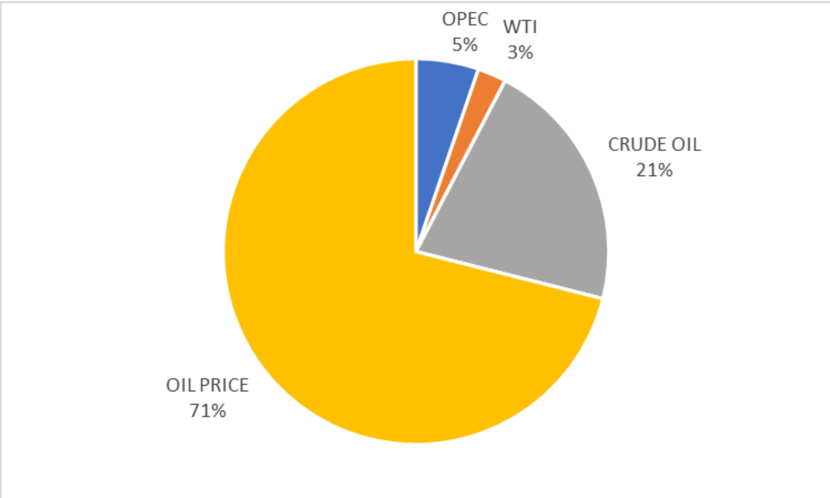

Figure 1. Distribution of indicator words

During the analysis, the keywords were examined without polarity. The keywords considered significant in the study were economic changes, market sentiment, and a set of words associated with oil price. The polarity of these words, whether they have a positive or negative effect on the future price of oil, was determined by the Neural Network. The analyzed words appeared a total of 2,835,321 times in the articles and were distributed as follows:

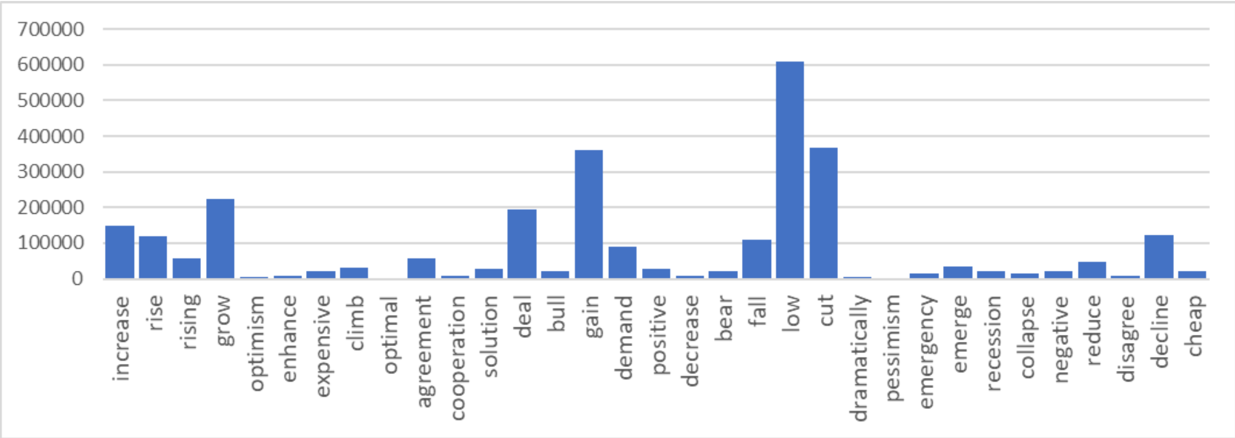

Figure 2. Distribution of indicator words

In the subsequent investigations, we disregarded the keywords that appeared without the corresponding indicator word, and assigned a count of zero to those instances. The number of indicator words used would become significant in the later stages of the analysis. Specifically, if an article didn't contain the required number of indicator words in the different runs, the occurrence of the keywords was not considered since based on the initial indication the article did not pertain to topics related to oil prices or oil producers. Therefore, further examination of such articles was deemed unnecessary.

2.2 Neural Network Method

In our study, we conducted a series of experiments with different settings for the Neural Network to predict the expected commodity market price change. Instead of looking at the specific oil price, we focused on the change in price compared to the previous trading day, taking into account inflation and general price level increases.

The first stage involved calculating the percentage of price change, followed by the article analysis in the second stage. We combined the values according to dates and days, and if an article was relevant, we calculated it and combined the keyword values on a daily basis.

We then combined the two prepared databases and conducted the tests. Our study spanned almost 15 years of time series data and articles, and the Neural Network looked for correlations based on keyword occurrence and co-occurrence, analyzing how they could affect the evolution of prices .

We evaluated the results based on an accepted margin of error, which determined the maximum percentage difference between the predicted and actual change. We also varied the number of indicator words required for an article to be considered valid. Additionally, we conducted two separate Neural Network analyses: one for every single day and the other for the days with indicator words related to the oil price.

Overall, we aimed to improve the method's accuracy and reduce errors. For each run, we evaluated the method's effectiveness in predicting not only the extent but also the sign of the future change.

3 Results

3.1 Neural Network method with no deletion

In terms of results, we first examine the "no deletion" method, that is, when we also consider the article days without the occurrence of the indicator in our ANN predictions. .

Table 1. Oil price prediction efficiency (without deletion)

Absolute percentage point difference	Success Rate | Ind:1	Success Rate | Ind:2	Success Rate | Ind:3	Success Rate | Ind:4	Success Rate | Ind:7	Success Rate | Ind:10	Success Rate | Ind13	Success Rate | Ind:16	Success Rate | Ind:20
0,02	0.57%	0.57%	0.83%	0.74%	0.57%	0.92%	0.74%	0.57%	0.96%
0,04	1.14%	1.18%	1.49%	1.57%	1.79%	1.92%	1.62%	1.44%	1.62%
0,07	1.79%	2.53%	2.66%	2.84%	3.01%	3.15%	3.19%	3.23%	3.45%
0,1	2.58%	3.71%	4.02%	4.11%	4.59%	4.89%	5.33%	5.29%	5.29%
0,15	4.06%	5.42%	5.37%	6.03%	6.82%	6.99%	7.12%	7.30%	7.08%
0,25	7.03%	8.87%	9.35%	9.65%	10.88%	11.66%	11.58%	11.88%	11.93%
0,4	11.66%	14.59%	14.81%	15.07%	16.34%	18.09%	17.78%	18.30%	18.79%
0,8	24.07%	26.69%	27.74%	28.00%	29.58%	31.94%	32.77%	34.21%	34.64%
1,2	34.78%	37.18%	37.18%	39.01%	42.07%	44.04%	46.18%	47.53%	48.36%
1,6	44.95%	46.70%	47.01%	49.98%	52.64%	55.18%	56.44%	58.85%	59.76%
2	54.48%	55.88%	55.48%	58.45%	61.38%	63.78%	65.66%	68.11%	68.98%
2,5	63.56%	64.88%	63.91%	67.37%	70.03%	72.56%	74.31%	76.89%	77.59%
3	70.51%	72.00%	71.56%	73.61%	76.10%	78.77%	80.43%	82.44%	83.66%
3,5	76.19%	76.85%	77.15%	78.51%	80.91%	83.36%	84.01%	86.28%	87.29%
4	80.43%	81.00%	81.48%	82.35%	85.28%	86.98%	87.46%	89.47%	90.61%
SIGN	63.52%	63.83%	65.09%	66.23%	68.98%	70.95%	71.56%	73.35%	73.66%

The findings suggest that the method employed is not suitable for highly accurate forecasting. Specifically, the study achieved less than 1% efficiency in predicting exchange rate changes with a maximum deviation of 0.02%, meaning that it was only able to accurately forecast the percentage change in exchange rates for 23 cases out of slightly over 6 years of examined data. However, the results also show that increasing the number of indicator words improves the efficiency of the method, as analyzing articles where indicator words occur more frequently leads to better results.

In addition, the effectiveness of sign prediction is also noteworthy, with a success rate of over 60% for minimal indicators and over 70% for 20 indicators, indicating a relatively effective performance. However, it should be noted that over the entire time frame from January 1, 1986, to May 16, 2021, the next day price was higher in 50.86% of cases. Thus, while the Neural Network's prediction is somewhat more effective, it cannot be used to make reliable investment decisions.

Of greater interest is the interpretation of error limits, as it is not necessarily crucial to obtain exact results, but rather to forecast the direction and magnitude of exchange rate changes within a certain degree of error.

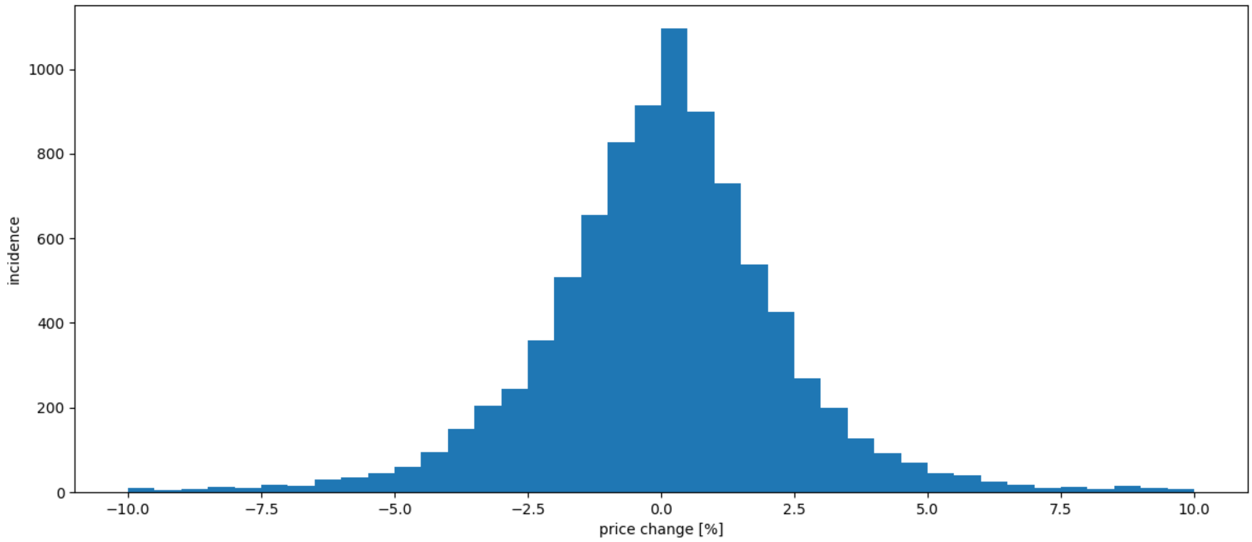

Figure 3. Distribution of daily exchange rate changes

The precision of forecasting can be sufficient for investor decision-making, even if the predicted outcome is not exact. By calculating possible error margins, we can accept a certain degree of imprecision. Figure 3. above illustrates the daily percentage changes of the oil price interval described earlier. In other words, a margin of error can be acceptable, as it may be appropriate to base investment decisions on outlier results. We can therefore focus on predicting major trend reversals or exceptional outcomes, rather than exact commodity price changes. For instance, if we allow for a deviation of 3 percentage points, we can consider everything with an absolute value greater than 3. In this case, the efficiency is over 80% for a high number of indicators.

One particular analysis method worth mentioning is the use of 13 indicators and a maximum deviation of 3 percentage points. With this approach, the following results are obtained:

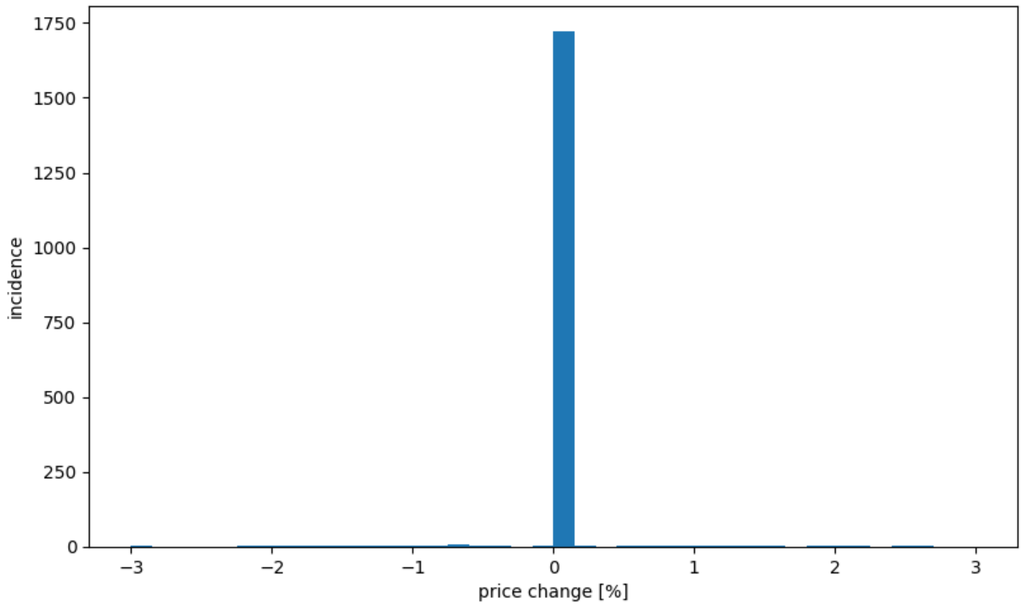

Figure 4. Distribution of predicted values when using 13 indicators, accepting a maximum deviation of 3%

It can be clearly seen that this type of Neural Network was able to effectively handle results close to zero, so it cannot be a basis for a prediction method.

3.2 Neural Network method with deletion

To improve the efficiency of our investigation, we attempted to streamline the dataset by removing the days on which no articles related to oil prices were published. This method was expected to eliminate unexpected events such as unanticipated price movements, resulting in a much cleaner dataset. In essence, this is similar to conducting commodity price analysis after the occurrence of an event, as it eliminates false results from the analysis conducted in the absence of the event.

Table 2. Oil price prediction efficiency (with deletion)

Absolute percentage point difference	Succes Rate | Ind:1	Succes Rate | Ind:2	Succes Rate | Ind:3	Succes Rate | Ind:4	Succes Rate | Ind:7	Succes Rate | Ind:10	Succes Rate | Ind13	Succes Rate | Ind:16	Succes Rate | Ind:20
0,02	0.74%	0.87%	0.61%	0.62%	0.43%	0.47%	0.00%	0.00%	1.54%
0,04	1.10%	1.56%	0.83%	1.24%	0.85%	0.71%	0.00%	0.00%	1.54%
0,07	2.10%	2.68%	1.97%	1.69%	1.28%	1.65%	0.42%	0.74%	4.62%
0,1	2.84%	3.05%	2.88%	2.57%	1.85%	2.12%	0.85%	0.74%	4.62%
0,15	4.00%	4.36%	3.94%	3.90%	2.56%	3.30%	2.12%	0.74%	4.62%
0,25	6.89%	6.48%	6.37%	6.48%	4.40%	6.13%	3.81%	2.96%	7.69%
0,4	11.57%	10.66%	10.77%	11.18%	8.24%	8.73%	7.20%	5.19%	10.77%
0,8	22.77%	22.19%	20.62%	21.83%	17.90%	15.33%	12.29%	14.81%	21.54%
1,2	33.33%	31.17%	31.54%	32.39%	25.00%	20.99%	19.92%	24.44%	32.31%
1,6	42.80%	39.84%	39.73%	42.86%	31.39%	28.07%	27.12%	32.59%	44.62%
2	50.32%	47.38%	48.37%	50.67%	36.36%	34.20%	34.75%	40.74%	47.69%
2,5	59.67%	55.24%	56.86%	57.59%	45.17%	42.92%	42.80%	45.19%	60.00%
3	66.40%	63.09%	63.38%	63.53%	54.40%	47.17%	50.85%	51.85%	67.69%
3,5	72.40%	71.07%	69.22%	71.16%	60.80%	54.01%	55.08%	59.26%	72.31%
4	77.71%	76.25%	74.07%	77.02%	68.04%	58.73%	61.44%	63.70%	81.54%
SIGN	62.46%	60.22%	57.47%	60.87%	53.12%	55.66%	56.36%	57.78%	63.08%

Through the implementation of the deletion method, the results have exhibited both improvement and deterioration under different basic settings, failing to yield a significant boost in prediction accuracy. In addition, the sign forecast has been notably compromised, indicating that this method does not effectively estimate the direction of future price changes.

Interestingly, the use of indicator 1 has generally demonstrated greater effectiveness compared to other indicators. To further explore this finding, we have also analyzed the distribution of the estimated changes in this scenario.

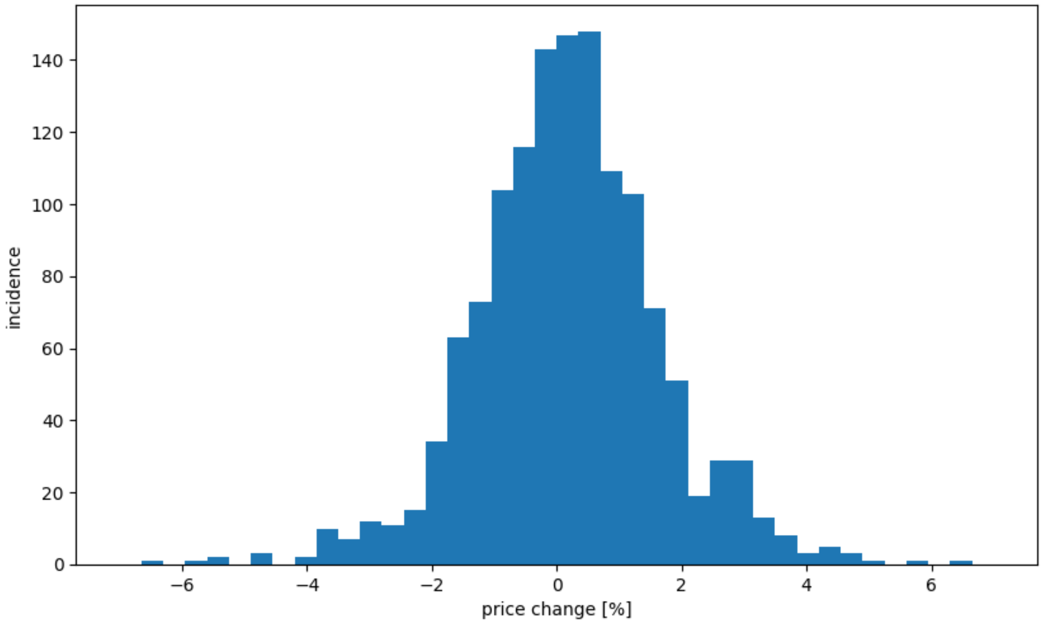

Figure 5. Distribution of predicted values when using 1 indicators, accepting a maximum deviation of 3%

The outcomes obtained in this scenario have a significantly wider range compared to the previously analyzed highlighted indicator number. Nevertheless, considering the error margin, it is still not appropriate to draw conclusive decisions from this analysis.

4 Discussion

To summarize, the analysis indicates a significant correlation between the Wall Street Journal articles and the future movement of oil prices. The current method provides a more efficient estimate of the sign of changes than random selection, but it is not precise enough to predict the exact extent of the change, particularly for results that are not close to zero.

To increase the effectiveness of the method, it is necessary to evaluate the selected keywords and their inclusion or exclusion, as well as the selection of indicator words. Additionally, the analysis of articles based on volume can be improved by using a Convolutional Neural Network or a summarized article analysis to increase efficiency.

Furthermore, incorporating historical data of the oil price as an additional factor in the Neural Network can improve accuracy. While the current research provides evidence of correlation and testability between the content of journal articles and exchange rate change, the method's accuracy and efficiency need further improvement.

Therefore, we consider the research concept to remain valid, and identify the need to expand and enhance our method. The goal is to increase the efficiency by testing different slimming options until a more efficient model is attained. Based on the current research, with appropriate development opportunities, efficiency can be increased to over 90%, which can be considered accurate for analyzing the price change of a commodity or stock that is influenced by numerous factors.

References

[1] Alaminos, D., Esteban, I., Salas, M. B., Callejón, A. M. (2020) Quantum Neural Networks for Forecasting Inflation Dynamics, Journal of Scientific & Industrial Research Vol. 79, February 2020, pp. 103–106. doi: 10.56042/jsir.v79i2.68439

[2] Baker, M. P., & Wurgler, J. A. (2007). Investor Sentiment in the Stock Market. SSRN Electronic Journal. doi:10.2139/ssrn.962706

[3] Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Financ. 61, 1645–1680.

[4] Barberis, N., Shleifer, A., Vishny, R., (1998). A model of investor sentiment. J. Financ. Econ. 4, 307–343.

[5] Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. Journal of Empirical Finance, 11(1), 1–27. doi:10.1016/j.jempfin.2002.12.001

[6] Dadgar Y., Keshavarz Gh., Tyataraj A., (2006). The Analysis of Relationship Between Inflation and Economic Growth in Iran, Journal of Economic Literature 5: 59-88.

[7] Daniel, K., & Titman, S. (1996). Evidence on the Characteristics of Cross Sectional Variation in Stock Returns. doi:10.3386/w5604

[8] DeLong, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., (1990). Noise trader risk in financial markets. J. Polit. Econ. 98, 703–738

[9] Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33(1), 3–56. doi:10.1016/0304-405x(93)90023-5

[10] Fama, E. F., & French, K. R.. (1996). Multifactor Explanations of Asset Pricing Anomalies. The Journal of Finance, 51(1), 55–84. doi:10.1111/j.1540-6261.1996.tb05202.x

[11] Fama, E.F., French, K.R., (1997). Industry cost of equity. J. Financ. Econ. 43, 153–193

[12] Fan, Y., Liang, Q., & Wei, Y.-M. (2008). A generalized pattern matching approach for multi-step prediction of crude oil price. Energy Economics, 30(3), 889–904. doi:10.1016/j.eneco.2006.10.012

[13] Galeshchuk, S., & Demazeau, Y. (2017). Forecasting hungarian forint exchange rate with convolutional neural networks. 2017 International Conference on Behavioral, Economic, Socio-Cultural Computing (BESC). doi:10.1109/besc.2017.8256358

[14] Gupta, R., & Kabundi, A. (2011). A large factor model for forecasting macroeconomic variables in South Africa. International Journal of Forecasting, 27(4), 1076–1088. doi:10.1016/j.ijforecast.2010.10.001

[15] Heidari H., and Parvin S., (2009). Modeling and Forecasting Iranian Inflation with Time Varying BVAR Models, Iranian Journal of Economic Research 36: 59-84.

[16] Jammazi, R., & Aloui, C. (2012). Crude oil price forecasting: Experimental evidence from wavelet decomposition and neural network modeling. Energy Economics, 34(3), 828–841. doi:10.1016/j.eneco.2011.07.018

[17] Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2000). Winter Blues: A SAD Stock Market Cycle. SSRN Electronic Journal . doi:10.2139/ssrn.208622

[18] Kumar, M., Moorthy, U., & Perraudin, W. (2003). Predicting emerging market currency crashes. Journal of Empirical Finance, 10(4), 427–454. doi:10.1016/s0927-5398(02)00068-3

[19] Langcake, S., & Robinson, T. (2017). Forecasting the Australian economy with DSGE and BVAR models. Applied Economics, 50(3), 251–267. doi:10.1080/00036846.2017.1319558

[20] Lemmon, M., Portniaguina, E., (2006). Consumer confidence and asset prices: some empirical evidence. Rev. Financ. Stud. 19, 1499–1529.doi: 10.1093/rfs/hhj038

[21] Madhou, A., Sewak, T., Moosa, I., & Ramiah, V. (2019). Forecasting the GDP of a small open developing economy: an application of FAVAR models. Applied Economics, 1–12. doi:10.1080/00036846.2019.1679346

[22] Mahdiani, M. R., & Khamehchi, E. (2016). A modified neural network model for predicting the crude oil price. Intellectual Economics, 10(2), 71–77. doi:10.1016/j.intele.2017.02.001

[23] Moshiri, S., & Cameron, N. (2000). Neural network versus econometric models in forecasting inflation. Journal of Forecasting, 19(3), 201–217. doi:10.1002/(sici)1099-131x(200004)19:3<201::aid-for753>3.0.co;2-4

[24] Moshiri, S., & Cameron, N. (2000). Neural network versus econometric models in forecasting inflation. Journal of Forecasting, 19(3), 201–217. doi:10.1002/(sici)1099-131x(200004)19:3<201::aid-for753>3.0.co;2-4

[25] Naderi, M., Khamehchi, E., Karimi, B., (2018) Novel statistical forecasting models for crude oil price, gas price, and interest rate based on meta-heuristic bat algorithm, Journal of Petroleum Science and Engineering, doi: 10.1016/j.petrol.2018.09.031.

[26] Neal, R., & Wheatley, S. M. (1998). Do Measures of Investor Sentiment Predict Returns? The Journal of Financial and Quantitative Analysis, 33(4), 523. doi:10.2307/2331130

[27] Nordhaus, W. D. (2011). The Economics of Tail Events with an Application to Climate Change. Review of Environmental Economics and Policy, 5(2), 240–257. doi:10.1093/reep/rer004

[28] Onimode, B., Alhassan, J., and Adepoju, S. (2015). Comparative study of inflation ratesforecasting using feed-forward artificial neural networks and auto-regressive (ar) models.International Journal of Computer Science Issues, 12.

[29] Scheinkman, J., Xiong, W., 2003. Overconfidence and speculative bubbles. J. Polit. Econ. 111, 1183–1219.

[30] Subecz, Z. (2019) Event Detection and Classification in Natural Texts, Gradus Vol 6, No 1 (2019) 16-21 ISSN 2064-8014

[31] Swaminathan, B. (1996). Time-Varying Expected Small Firm Returns and Closed-End Fund Discounts. Review of Financial Studies, 9(3), 845–887. doi:10.1093/rfs/9.3.845

[32] Thakur, G. S. M., Bhattacharyya, R., & Mondal, S. S. (2016). Artificial Neural Network Based Model for Forecasting of Inflation in India. Fuzzy Information and Engineering, 8(1), 87–100. doi:10.1016/j.fiae.2016.03.005

[33] Tkacz, G. (2001). Neural network forecasting of Canadian GDP growth. International Journal of Forecasting, 17(1), 57–69. doi:10.1016/s0169-2070(00)00063-7