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EVALUATION OF OPTIMAL ECONOMIC AND TECHNICAL INDICATORS FOR AGRICULTURE STOCK TRADING DECISION

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Abstract: *The main goal of the research was to determine which indicators are the most impactful on the buy and sell triggers of stocks to maximize profits of the trade. The aim was to determine the agriculture stock price movements based on economic and technical indicators. The investors in the stock market want to maximize trade profits by buying or selling the stocks. Technical and economic analyses are conducted to determine whether to sell or buy agriculture stocks. Since many factors could impact stocks profit decisions, it is essential to determine which parameter has more or less influence on the decision. For such a purpose adaptive neuro-fuzzy inference system (ANFIS) was used since the method is suitable for redundant and nonlinear data. Generally, technical indicators are more valuable and impactful for agricultural stock trading decision-making. Technical indicator moving average convergence and divergence (MACD) strongly influences the stock trading decision. Economic indicator relative change after smoothing 15 days federal rate has the most decisive influence on the stock trading decision.*

Keywords: *stock profit; trading; economic; decision; ANFIS; agriculture*

JEL: *O12, R53*

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PROCENA OPTIMALNIH EKONOMSKIH I TEHNIČKIH INDIKATORA ZA DONOŠENJE ODLUKE O TRGOVANJU POLJOPRIVREDNIM AKCIJAMA

Sažetak: *Cilj istraživanja je utvrđivanje indikatora koji imaju najveći uticaj na kupovinu i prodaju akcija radi maksimiranja dobiti koja nastaje u trgovini. Autori su se orijentisali na određivanje kretanja cena poljoprivrednih akcija na osnovu ekonomskih i tehničkih indikatora. Investitori na berzi žele da maksimiraju dobit od trgovine putem prodaje i kupovine akcija. Primenom određenih tehničkih i ekonomskih analiza može se doneti odluka o prodaji i kupovini poljoprivrednih akcija. S obzirom na to da postoje mnogi faktori koji utiču na odluku o dobiti od akcija, veoma je važno odrediti koji parametri ispoljavaju veći, a koji manji uticaj na donošenje odluke. U tu svrhu je primenjen adaptive neuro-fuzzy inference system (ANFIS), s obzirom na to da je ovaj metod prikladan za redundantne i nelinearne podatke. Uopšteno govoreći, tehnički indikatori su znatno korisniji i moćniji za donošenje odluke u oblasti trgovine poljoprivrednim akcijama. Tehnički indikator konvergencije i divergencije pokretnog proseka (Technical indicator moving average convergence and divergence - MACD) ima najjači uticaj na donošenje odluke o trgovanju akcijama. Relativna promena ekonomskog indikatora, nakon petnaestodnevnog saveznog kursa ima najpresudniji uticaj na odluku o trgovanju akcijama.*

Ključne reči: *dobit od akcija, trgovanje, odluka, ANFIS, poljoprivreda*

1. INTRODUCTION

Stock prices forecasting is of primary interest in different fields like finance, trading and statistics. The main goal of investors in the stock market is to maximize trade profits through buying or selling of the investment. Technical and fundamental analyses are conducted when making the selling or buying decision. Profits, growth rates, market position, etc., are considered in fundamental analysis. Fluctuation of price is considered in technical analysis.

Numerous papers investigate whether a particular magnitude and direction of inter-regional return signal transmission dominate the performance of trading in stock markets (Brzeszczyński & Ibrahim, 2019; Ziadat, Herbst, & McMillan, 2020; Bhuyan, Robbani, Talukdar, & Jain, 2016; Sheng, Brzeszczyński, & Ibrahim, 2017; Yarovaya, Brzeszczyński, & Lau, 2016; Bohl, Brzeszczyński, & Wilfling 2009; Bohl & Brzeszczyński, 2006). Firms with more trade credit show lower stock price synchronicity, verifying the information content of trade credit (Liu & Hou, 2019). It is unlikely or risky for a rational investor to rely on forecast outliers to trade stocks (Zhang, Zhong, Dong, Wang, & Wang 2019). Individuals have long been blamed for noise trader noise risk (Park, Choi, & Choi, 2019). News reports have become an imperative conduit of public information. Empirical analysis reveals that the news variables provide helpful information for predicting stock market returns (Wu, Hou, & Lin, 2019a; Wu, Hou, & Lin, 2019b; Yin, & Feng, 2019; Ciner, 2019; Narayan, Sharma & Thuraisamy, 2015; Oliveir, Cortez. & Areal, 2017). Around 32% react statistically significantly to oil prices, dispelling the common notion that oil prices affect the stock market homogeneously (Narayan, Phan & Sharma, 2019). The fuzzy approach makes it possible to account for the vagueness and uncertainty of the pattern features in a stock trading system (Naranjo, Arroyo, & Santos, 2018; Naranjo & Santos, 2019; Chang, Wu, & Lin, 2016; Chen, 2014; Chourmouziadis & Chatzoglou, 2016; Lincy & John, 2016; Sevastianov & Dymova, 2009; Vella & Ng, 2014).

The study's primary goal is to analyze which economic and technical indicator is the most influential on the agriculture stock trading decisions. During the analysis, the economic fluctuation and business environment are considered. This study uses the adaptive neuro-fuzzy inference system (ANFIS) (Jang, 1993; Petković, Issa, Pavlović, Pavlović, & Zentner, 2012) to estimate parameters' influence on agriculture stock trading decisions. ANFIC methodology is used because of the high nonlinearity between input and output parameters. As input parameters, technical and economic factors are used. The output is agriculture stock trading decision (sell or buy).

2. LITERATURE OVERVIEW

Determination of trading agriculture stocks decisions is challenging because of many different factors. Stock trading decisions are vital in finance, trading, and statistics. The main goal of investors in the stock market is to maximize trade profits through buying or selling of the investment.

Networks derived from agriculture stock prices are often used to model developments on financial markets. They are tightly intertwined with crises, but the influence of changing market topologies on the broader economy (i.e., GDP) is unclear (Heiberger, 2018). Several methods have been developed to detect stock trading signals, but artificial intelligence methods have drawn more and more attention from both investors and researchers (Chen & Hao, 2018). The success of the stock selection is contingent upon the future performance of stock markets (Yang, Chen, & Tang, 2019). Deep learning has recently achieved great success in financial areas such as stock market prediction, portfolio optimization, financial information processing and trade execution strategies (Zhang, Zhong, Dong, Wang, & Wang 2019). Predictive stock price systems aim to provide abnormal returns for financial market operators and serve as a basis for risk management tools (Henrique, Sobreiro, & Kimura, 2018).

Li and Luo (2020) propose an intelligent stock-trading decision support system by using rough cognitive reasoning, based on which stocks with the higher probabilities of rising in the short term after the occurrences of limit-up can be distinguished. Forecasting the direction of the daily changes of stock indices is an essential yet challenging task for market participants (Zhou, Zhang, Sornette, & Jiang, 2019). With the arrival of the low-interest rates, investors entered the stock market to seek higher returns. However, the stock market proved volatile, and only rarely could investors gain excess returns when trading in real-time (Chang & Lee, 2017). Predicting the direction and movement of stock index prices is difficult, often leading to excessive trading, transaction costs, and missed opportunities (Chiang, Enke, Wu, & Wang, 2016; Chang, Liao, Lin, & Fan, 2011; Huang, Goto, & Nakamura, 2004).

3. MATERIALS AND METHODS

As technical indicators moving average convergence and divergence (MACD), Stochastic K%D, Relative strength index (RSI), Larry Williams Percent Range (William R %) are used based on the literature source (Behl, Tondehal, & Zaman, 2018). As economic indicators, the Consumer price index (CPI), Producer price index (PPI), Funds Rate and Delta Volume are used based on the literature source (Behl et al., 2018). Williams Percent Range is a type of momentum indicator which measures overbought and oversold levels. Delta Volume is an indicator that can identify where the next move is likely to go. Stochastic K%D indicators are indicators in technical analysis which belong to oscillators and measure the relative position of the closing prices compared to the amplitude of price oscillations in a given period. Daily closing prices and volume data are used for calculating the technical indicators. The closing prices and volume data are smoothened by Welles Wilder Smoothing, and a relative 15-day change is calculated as a basis for price and volume trend indicators. The economic indicators are acquired from World Bank Database based on the European Union countries. The outputs are buy (1) and sell (0) decisions. The period of the dataset is 1990-2017. MATLAB Software has been used for the statistical analysis of the data.

Table 1

Data samples

Days	**1** Daily Federal Rate	**2** Relative Change after Smoothing 15 days Federal Rate	**3** CPI	**4** PPI	**5** Delta Volume	**6** RSI	**7** MACD	**8** William R %	**9** Stochastic K %	**10** Stochastic D %	**11** Change After Smoothing 15 days	**Output** Decisio
1	8.2	-0.2987	0.2	0.43821	-2.1353	52.1769	-0.225	-0.1401	99.8599	77.6805	-0.1534	Buy - 1
2	8.18	-0.3241	0.2	0.43821	3.2184	58.5637	0.2741	-1.436	98.5639	90.3682	-0.1219	Buy - 1
3	8.23	-0.3201	0.2	0.43821	7.2898	66.8343	0.7391	-6.7364	93.2636	97.2292	-0.0679	Buy - 1
4	8.24	-0.3162	0.2	0.43821	56.6319	84.9749	1.7475	-1.2627	98.7372	96.8549	0.0579	Buy - 1
5	8.27	-0.2953	0.2	0.43821	49.3373	88.0974	2.7371	-11.9413	88.0587	93.3532	0.2017	Buy - 1
6	8.34	-0.2581	0.2	0.43821	9.5837	86.1083	3.4437	-13.4747	86.5253	91.1071	0.33	Buy - 1
7	7.53	-0.4173	0.2	0.43821	5.5496	84.9006	3.9357	-14.3883	85.6117	86.1071	0.4489	Buy - 1
8	8.2	-0.4043	0.2	0.43821	8.6338	97.2077	4.3138	-12.8548	87.1452	96.4274	0.5909	Buy - 1
9	8.22	-0.3987	0.2	0.43821	6.9973	97.0403	4.5745	-13.6544	86.3456	86.3674	0.7212	Buy - 1
10	8.24	-0.3593	0.2	0.43821	9.2658	97.2477	4.9946	-3.9748	96.0252	89.8387	0.8602	Buy - 1
11	8.22	-0.2339	0.2	0.43821	32.7326	97.053	5.3011	-7.9524	92.0476	91.4728	0.9856	Buy - 1
12	8.24	-0.2172	0.2	0.43821	12.2047	97.0261	5.5495	-4.7769	95.2231	94.4319	1.1071	Buy - 1
13	8.29	-0.1934	0.2	0.43821	0.9918	92.9983	5.6106	-9.3345	90.6655	92.6454	1.2039	Buy - 1
14	8.27	-0.1799	0.2	0.43821	-21.3791	78.1337	5.2891	-29.1196	70.8804	85.5897	1.2632	Buy - 1
15	8.26	-0.1617	0.2	0.43821	-9.9757	81.529	5.4611	0	100	87.1819	1.3484	Buy - 1
16	7.69	-0.2773	0.2	0.43821	29.9289	81.1203	5.5503	-7.1833	92.8167	87.899	1.4279	Buy - 1
17	8.23	-0.2718	0.2	0.43821	7.7178	80.7271	5.5866	-5.5857	94.4143	95.7437	1.5022	Buy - 1
18	8.28	-0.2567	0.8	-0.26178	21.5927	75.2717	5.7052	-3.1114	96.8886	94.7066	1.5371	Buy - 1
19	8.28	-0.2491	0.8	-0.26178	13.2973	76.8349	6.0714	-2.8303	97.1697	96.1576	1.5798	Buy - 1

	1 Daily Federal Rate	**2** Relative Change after Smoothing 15 days Federal Rate	**3** CPI	**4** PPI	**5** Delta Volume	**6** RSI	**7** MACD	**8** William R %	**9** Stochastic K %	**10** Stochastic D %	**11** Change After Smoothing 15 days	**Output** Decisio
20	8.27	-0.2611	0.8	-0.26178	28.1769	75.9011	6.2285	-12.7153	87.2847	93.781	1.6198	Buy - 1
21	8.22	-0.0887	0.8	-0.26178	5.1608	71.6943	6.1466	-23.4933	76.5067	86.987	1.6508	Buy - 1
22	8.25	-0.0748	0.8	-0.26178	2.7502	66.3158	5.8679	-34.6249	65.4751	76.3889	1.6675	Buy - 1
23	8.26	-0.0636	0.8	-0.26178	-8.4715	56.5921	5.2286	-67.1335	32.8667	58.2495	1.6566	Buy - 1
24	8.26	-0.0575	0.8	-0.26178	-22.9075	55.9645	4.901	-49.4457	50.5533	49.5983	1.643	Buy - 1
25	8.23	-0.0539	0.8	-0.26178	1.2804	61.294	4.9571	-17.4965	82.5035	55.3078	1.6544	Buy - 1
26	8.61	0.0369	0.8	-0.26178	2.3971	57.9891	4.8368	-26.8327	73.1673	68.7413	1.6524	Buy - 1
27	8.29	0.0362	0.8	-0.26178	-12.2941	56.1965	4.5279	-40.6639	59.336	71.6689	1.644	Buy - 1
28	8.29	0.0404	0.8	-0.26178	31.6556	62.8509	4.2351	-41.2508	58.7492	63.7508	1.6587	Buy - 1
29	8.28	0.0444	0.8	-0.26178	-14.0906	44.1767	3.4764	-100	0	39.3617	1.6015	Buy - 1
30	8.25	0.1797	0.8	-0.26178	-12.9218	46.4693	2.9692	-81.8253	18.1747	25.6413	1.5536	Sell - 0
31	8.24	0.1785	0.8	-0.26178	-11.1137	46.8686	2.5883	-76.8253	23.1747	13.7831	1.5083	Buy - 1
32	8.25	0.1676	0.8	-0.26178	-10.1836	45.9791	2.3696	-65.8253	34.0477	25.1323	1.4605	Buy - 1
33	8.24	0.1546	0.8	-0.26178	11.5895	32.5256	1.7692	-99.1092	0.8908	19.3711	1.3593	Buy - 1
34	8.3	0.1588	0.8	-0.26178	-13.5936	30.4288	1.0297	-97.3959	2.6041	12.5142	1.2466	Buy - 1
35	8.33	0.1823	0.8	-0.26178	-8.1451	31.6657	0.4187	-98.6382	1.3618	1.6189	1.45	Buy - 1
36	8.39	0.2127	0.8	-0.26178	-4.6767	39.6657	0.1809	-75.6234	24.3766	9.4475	1.074	Buy - 1
37	8.36	0.2327	0.8	-0.26178	-11.2991	48.4348	0.1912	-60.0997	39.9003	21.8796	1.0456	Buy - 1
38	8.32	0.2426	0.8	-0.26178	-5.0819	44.3541	0.2282	-57.6684	42.3316	35.5362	1.003	Buy - 1

Note. World Bank Database

ANFIS network has five layers, as shown in Figure 1. The main core of the ANFIS network is the fuzzy inference system. Layer 1 receives the inputs and converts them into the fuzzy value by membership functions. In this study, the bell-shaped membership function is used since the function has the highest capacity for the regression of the nonlinear data.

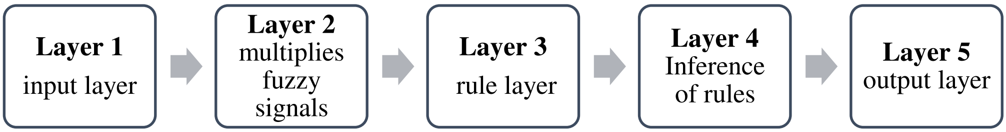

Figure 1. ANFIS layers

Note. Jang, J. S. (1993). ANFIS: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics*, *23*(3), 665-685.

Bell-shaped membership functios is defined as follows:

$$\mu(x) = bell(x; a_i, b_i, c_i) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}} \tag{1}$$

where $\{a_i, b_i,\ c_i\}$ is the parameters set, and x is input.

The second layer multiplies the fuzzy signals from the first layer and provides the firing strength of a rule. The third layer is the rule layer, where all signals from the second layer are normalized. The fourth layer provides rules inference, and all signals are converted in crisp values. The final layers summarized all the signals and provided the crisp output value.

3. RESULTS

Figure 2 and Table 2 show the influence of the single parameters on the selling or buying decision of stocks. One can see the visual difference between prediction errors of the single parameters based on prediction errors (trn – Training, chk - Checking). Training RMSE shows the influence of the inputs on stocks' selling or buying decisions. Smaller training error more influence on the decision (Nikolić, Mitić, Kocić, & Petković, 2017; Petković, Petković, Kuzman, Milovančević, Wakil, Ho, & Jermsittiparsert, 2020; Cao, Zandi, Rahimi, Petković, Denić, Stojanović, & Assilzadeh, 2021; Stojanović, Petkovic, Alarifi, Cao, Denic, Ilic, & Milickovic, 2021; Kuzman, Petković, Denić, Petković, Ćirković, Stojanović, & Milić, 2021; Petković, Barjaktarovic, Milošević, Denić, Spasić, Stojanović, & Milovancevic, 2021). Checking RMSE is used for overfitting tracking between training and checking data. Here, there is no overfitting since checking errors track training errors. As can be seen, the smallest training error is for input parameter seven or selling or moving average convergence and divergence (MACD), which belongs to the technical indicators. Therefore, the marketing co MACD has the strongest influence when making agricultural stocks on the selling or buying decision (Anghel, 2015). The first economic indicator which has the strongest influence on the decision is parameter 2 or Relative Change after Smoothing 15 days Federal Rate (Behl et al., 2018). The parameter 5, or delta volume, has the highest training error or the smallest influence on agriculture stocks' selling or buying decisions (Behl et al., 2018).

Table 3 shows prediction errors based on two inputs combinations where one can see that parameters 8 and 11 have the smallest training error, therefore the highest impact on selling or buying decision of agriculture stocks. It means the combination of William R % and Change after Smoothing 15 days forms the optimal combination of stocks' selling or buying decision (Behl et al., 2018). Generally, technical indicators are more useful and impactful for decision-making in stocks trading (Behl et al., 2018).

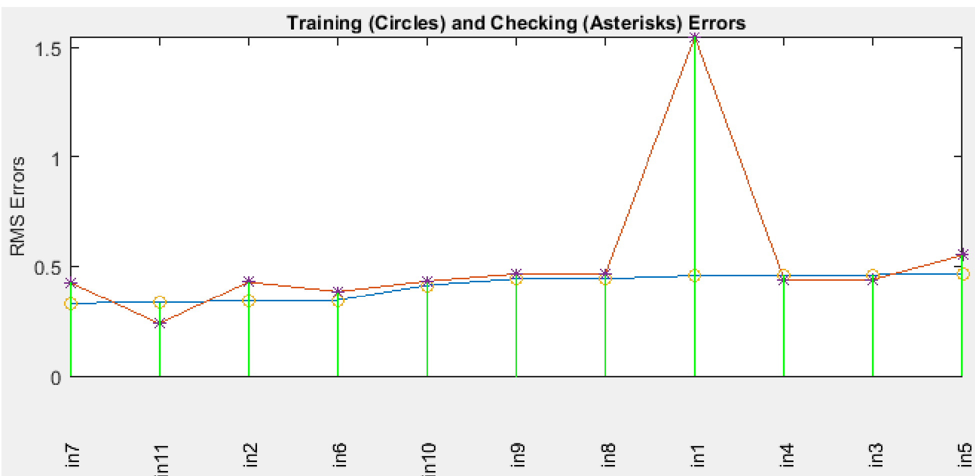

Figure 2. Single input influence on selling or buying decision of stocks

Note. Authors' calculations (MATLAB Software)

Table 2

Correlation matrix of input influence on selling or buying decision of agriculture stocks

	Daily Federal Rate	Relative Change after Smoothing 15 days Federal Rate	CPI	PPI	Delta Volume	RSI	MACD	William R %	Stochastic K %	Stochastic D %	Change After Smoothing 15 days
Daily Federal Rate	trn=0.4586, chk=1.5505										
Relative Change after Smoothing 15 days Federal Rate	trn=0.3322, chk=0.8931	trn=0.3447, chk=0.4289									
CPI	trn=0.4304, chk=1.1447	trn=0.2766, chk=0.3682	trn=0.4620, chk=0.4413								
PPI	trn=0.4303, chk=1.1423	trn=0.2766, chk=0.3682	trn=0.4620, chk=0.4413	trn=0.4620, chk=0.4413							
Delta Volume	trn=0.3957, chk=1.7467	trn=0.2452, chk=6.2242	trn=0.3944, chk=10.1003	trn=0.3944, chk=9.9976	trn=0.4676, chk=0.5511						
RSI	trn=0.2798, chk=2.0772	trn=0.1820, chk=0.4144	trn=0.2461, chk=0.3426	trn=0.2461, chk=0.3426	trn=0.2324, chk=9.4868	trn=0.3455, chk=0.3852					
MACD	trn=0.3048, chk=2.2631	trn=0.2489, chk=0.3298	trn=0.2543, chk=0.2997	trn=0.2543, chk=0.2997	trn=0.2484, chk=0.7415	trn=0.1192, chk=0.3997	trn=0.3326, chk=0.4272				
William R %	trn=0.3832, chk=1.9698	trn=0.2637, chk=0.4318	trn=0.3102, chk=0.3874	trn=0.3102, chk=0.3873	trn=0.2550, chk=20.6326	trn=0.2296, chk=0.3908	trn=0.2772, chk=0.3989	trn=0.4440, chk=0.4664			
Stochastic K %	trn=0.3846, chk=1.5864	trn=0.2637, chk=0.4319	trn=0.3102, chk=0.3902	trn=0.3102, chk=0.3901	trn=0.2550, chk=18.0037	trn=0.2296, chk=0.3910	trn=0.2772, chk=0.3988	trn=0.4195, chk=1.8761	trn=0.4440, chk=0.4663		
Stochastic D %	trn=0.3588, chk=0.9366	trn=0.2677, chk=0.5353	trn=0.2916, chk=0.3506	trn=0.2916, chk=0.3506	trn=0.2974, chk=6.1279	trn=0.1989, chk=0.5037	trn=0.2512, chk=0.3837	trn=0.2732, chk=0.8324	trn=0.2727, chk=0.8572	trn=0.4143, chk=0.4327	
Change After Smoothing 15 days	trn=0.3179, chk=2.2628	trn=0.1923, chk=0.3069	trn=0.2332, chk=0.2558	trn=0.2333, chk=0.2565	trn=0.2817, chk=1.8368	trn=0.1344, chk=0.4137	trn=0.1444, chk=0.3517	trn=0.1089, chk=0.4742	trn=0.1091, chk=0.4597	trn=0.1434, chk=0.3612	trn=0.3348, chk=0.2398

Note. Authors' calculations (MATLAB Software)

Figure 3 shows ANFIS prediction of selling or buying decisions of agriculture stocks for selected one input. One can note the medium correlation between real and predicted points based on the coefficient of determination. Figure 4 shows ANFIS output points versus real points of agriculture stocks' selling or buying decisions. Blue circles represent training data, while red asterisk represents the ANFIS prediction.

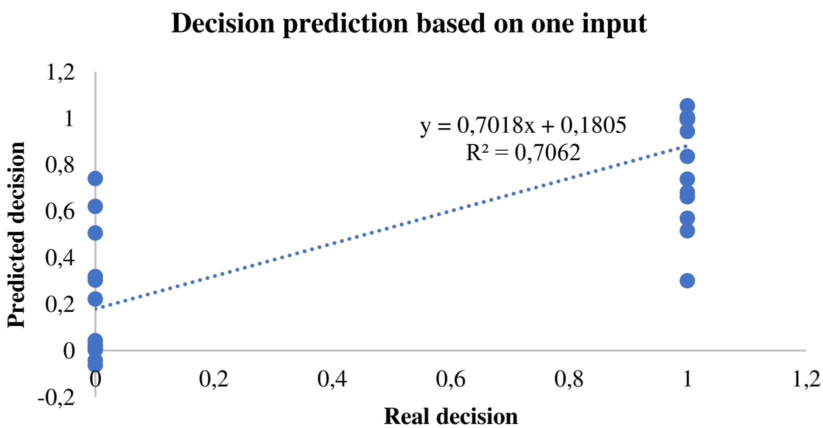

Figure 3. ANFIS predicted trading decisions based on one selected input

Note. Authors' calculations (MATLAB Software)

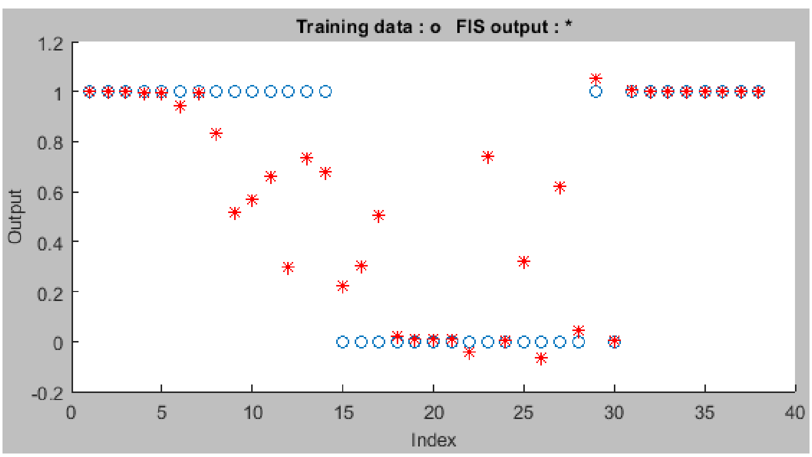

Figure 4. ANFIS output points vs. real points based on one selected input

Note. Authors' calculations

Figure 5 shows ANFIS prediction of selling or buying decisions of agriculture stocks for two inputs. One can note a strong correlation between real and predicted points based on the coefficient of determination. Figure 6 shows ANFIS output points versus real points of agriculture stocks' selling or buying decisions. Blue circles represent training data, while red asterisks represent the ANFIS prediction.

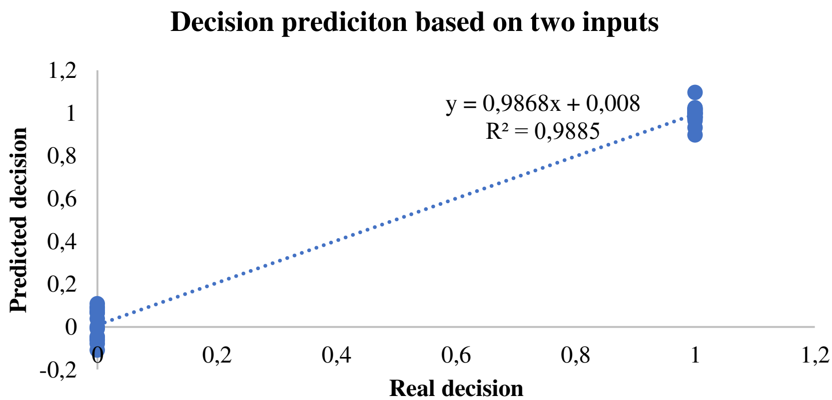

Figure 5. ANFIS predicted trading decisions based on two selected input

Note. Authors' calculations (MATLAB Software)

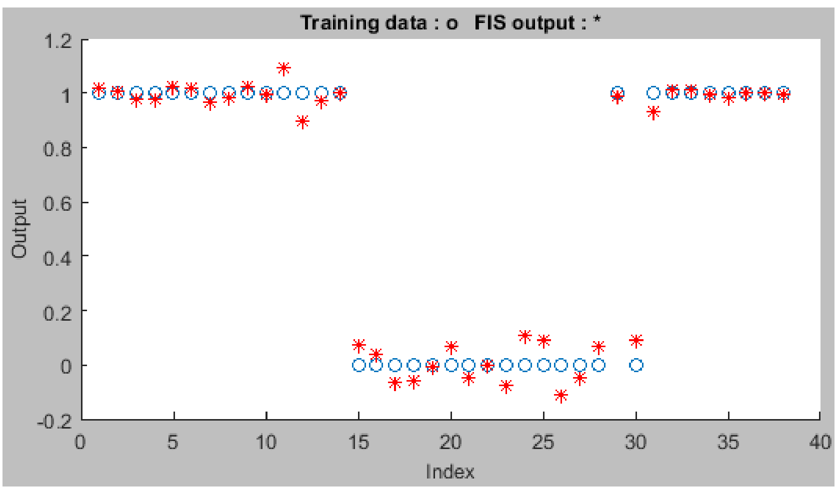

Figure 6. ANFIS output points vs. real points based on two selected input

Note. Authors' calculations

4. DISCUSSION

Predicting stocks is complex and challenging. The economic indicators helped in identifying the beginning and end of recession periods. Different labeling techniques were tried, starting with two labels - buy and sell – on a daily basis. However, such labels are hard for the model to understand and correlate based on the feature set used. The data was then labeled based on prices and the overarching business cycle trends. As the objective function has been to optimize stock returns. Hence not all mistakes

made by the model are equal. The obtained results in the article represent the new approach for the stock trading decision, and so far, nobody has examined a similar investigation.

5. CONCLUSION

There are technical and economic analyses to determine the selling of buying decisions of the agriculture stocks. This article presents a selection procedure to determine the most influential technical and economic parameters of the selling or buying decision of the stocks. Since many factors could impact agriculture stock's profit decision, it is crucial to determine which parameter has more or less influence on the decision.

This study used an adaptive neuro-fuzzy inference system (ANFIS) for selection procedure to determine the selling of buying decisions of the agriculture stocks based on technical and economic indicators. Generally, technical indicators are more useful and impactful for agricultural stock trading decision-making.

For future research, the data set can be extended to increase the train, dev, test data. Translating the objective function of maximizing profits into a cost function, which is directly applied to the models, should further improve the targeted results. Additional optimization can be done by improving the cost function that penalizes the more severe misclassifications and using the random forest for feature selection. This predictive framework can be extended to other stock market indexes.

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