ASEJ ISSN: 2543-9103 ISSN: 2543-411X (online)

The accuracy of forecasting neural networks and the impact of using fuzzy sets for the currency market

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***Abstract*— The aim of the article is to check the accuracy of forecasts of neural networks on the currency market and the impact of fuzzy sets on their accuracy. The study presented in this article uses an original approach that considers the use of neural networks and fuzzy sets in the mechanism of investment decision making. The empirical study is based on projections of the three currency pairs of the Swiss franc, British pound, and the dollar against the euro. These currencies are forecasted using three different neural networks - ELM, MLP and LSTM, for ten different forecast horizons (from 1 to 10 days). In forecasting, neural networks use historical data, both for price levels and rates of return. The research carried out confirmed that the presented method is in many cases more accurate than the methods compared to it in this study.**

Keywords— neural networks, fuzzy sets, currency market, forecasting

I. INTRODUCTION

Exchange rates and their fluctuations play a key role in the economy in times of globalization. It is believed that exchange rates have a real and significant impact on the current situation of the economy in each country (Schrimpf & Sushko, 2020). Forecasting exchange rates is an important issue both for speculative opportunities and thus profit-generating (Markova, 2019), and for securing positions in international trade. The methods of technical and fundamental analysis can be used for forecasting (Nti, 2020). However, due to the non-linear, dynamic and chaotic price behavior in the markets and the related difficulties in forecasting their changes, other methods are more and more often used (Zhang & Wan, 2007, Henrique et al., 2019). The most frequently used metods are: Artificial Neural Networks, Support Vector Machine, Neural Network and Machine Learning Methods (Gandhmal & Kumar, 2019). Neural networks and machine learning techniques are very widely used to forecast changes in the markets (Alakhras, 2005, Strader et al., 2020), including forecasting changes in the currency markets. In forecasting, neural networks and hybrid neural networks (Hao & Gao, 2020) are used to connect neural networks with other methods to improve the accuracy of forecasts.

This article focuses on the use of neural networks and fuzzy sets to forecast exchange rate movements. The purpose of this study is to make a decision to invest in growth or decline. In connection with this approach, the most important thing in the study is a binding decision on the forecast of change in the exchange rate direction. My approach has a different specificity than the use of neural-fuzzy networks, also used in many studies to forecast financial time series (Kodogiannis & Lolis, 2002) and those related to the currency market (Babu & Reddy, 2015). Fuzzy neural networks combine fuzzy modeling with the structure of artificial neural networks. The goal of teaching these networks is to discover fuzzy rules, membership functions, input, and output variables. In this approach, the decision-making process operating on fuzzy rules outside the neural network.

The aim of the study is to check whether the accuracy of forecasts improves thanks to the applied method, which may translate into a positive impact on the improvement of generated profits when investing in currency pairs or the possibility of using it in hedging positions on the currency market. Additionally, the presented approach eliminates the problem of choosing one setting and one neural network and creates the possibility of using multiple forecasts for a given day in order to make one binding decision based on them. The empirical study confronts the results of the accuracy of

ASEJ - Scientific Journal of Bielsko-Biala School of Finance and Law
Volume 28, No 1 (2024), pages 8
https://doi.org/10.19192/wsfip.sj1.2024.3
Received: December 2023 Accepted: March 2024
Published: March 2024

forecasts made using neural networks with the results of the accuracy of forecasts modified using fuzzy sets. Three types of neural networks are used in the study: Extreme Learning Machines (ELM), Multilayer Perceptrons (MLP) and Long Short-term Memory (LSTM). Based on the study, it was found that the presented method for selected currency pairs and using forecasts with the above-mentioned networks in many cases has a higher accuracy than the methods compared to it in this study.

The layout of the rest of the article is as follows. The next section describes the proposed forecasting approach using neural networks and fuzzy sets. Then, the basic characteristics of the data used in the empirical study are presented. Finally, the forecasting results will be presented in comparison with the forecasts obtained by the majority network method and the average accuracy of the neural networks. The final section contains conclusions.

II. Methodology

Forecasting currency prices is made based on price levels and returns of their historical data with the use of neural networks. Three different neural networks were used in the study. These networks are:

- ELM - Extreme Learning Machines (Rumelhart, 1986)
- MLP - Multilayer Perceptrons
- LSTM - Long short-term memory (Hochreiter & Schmidhuber, 1997)

For each of the less complex neural networks (ELM and MLP), 49 different combinations of neural network settings were used and for the LSTM 42 different combinations, which gives a total of 140 different series of forecasts. The parameters that are part of the network settings are the number of lags (lags - number of lags) and the number of hidden nodes (hd - number of hidden nodes). Both parameters can have seven different values. The number of hidden nodes takes the values (2,5,10,15,20,25,50) and the number of delays used in the neural network takes the values (1,2,3,4,5,6,7). The number of hidden nodes was adopted not as consecutive natural numbers, but with keeping certain intervals to search for optimal orders of magnitude of nodes and to investigate the dependence of the forecast results on this parameter.

Thanks to such settings, the paper answers the question whether increasing the number of hidden nodes has a positive impact on the results of neural networks, and if so, to what level it is profitable to increase them, so that the benefits of improving the results are greater than the computational load resulting from the use of multiple hidden nodes. The use of the number of delays in the range from one to seven results from the nature of research on financial markets and the support for such an approach in the selection of this parameter can be found in many scientific studies (De Myttenaere et al., 2015). The LSTM network omitted to set the hidden nodes to 5, due to its complexity (Moghar & Hamiche, 2020). Each day the forecast is made for ten different horizons (from 1 to 10 days).

In order to check whether the accuracy of the forecasts improves thanks to the method used, the accuracy results obtained using only neural networks are confronted with the results in which the final forecast is adjusted using fuzzy sets.

The concept of fuzzy set was introduced by L.A. Zadeh, in his work (Zadeh, L., A., 1965). It was a generalization of the notion of an ordinary set. In the normal set, the logical value is contained in the {0.1} set, while in the fuzzy set, the logical value belongs to the unit range from zero to one - I = [0,1]. The fuzzy set Z is a function that assigns to each element x∈X its degree of belonging to the fuzzy set Z:

$$\mu_z(x): x \to [0,1]$$

where: $\mu\ (x)$ is the membership function of the fuzzy set Z. The value of the function $\mu\ (x)$ can take values within the range of [0,1] and characterizes the degree of membership of the element x to a given fuzzy set Z. If $\mu\ (x)\ =\ 1$, we talk about full membership of the fuzzy set Z, $\mu\ (x)\ =\ 0$ means that the element x does not belong to the fuzzy set Z, while values between 0 and 1 mean partial membership. (Lazzerini et al., 2000)

The height of the fuzzy set is the maximum value that the membership function assumes in the entire consideration space of set X. The fuzzy set is also characterized by the carrier of the fuzzy set, which is an unfocused subset of the set Z, all elements of which have a non-zero degree of belonging to the set Z, i.e., $\mu\ (x) >\ 0$. On the other hand, the non-fuzzy subset composed of elements with the membership degree 1 is called the kernel of the fuzzy set. These dependencies are presented in Figure 1.

The membership function of the fuzzy set is the function that assigns each element $x\ \in X$ the degree of belonging to the fuzzy set Z. Two basic types of membership functions used in the empirical study, i.e., triangular, and trapezoidal, will be described below.

The triangular membership function is expressed by the formula:

$$\mu(x;a,b,c) = \begin{cases} 0\ dla\ x\ \le a \\ \dfrac{x-a}{b-a}\ dla\ a < x\ \le b \\ \dfrac{c-x}{c-b}\ dla\ b\ \le x\ < c \\ 0\ dla\ x\ \ge c \end{cases}$$

The triangular membership function is a special example of a trapezoidal membership function (Figure 1. Illustrating the basic elements characteristic of fuzzy sets can be considered an example of a trapezoidal membership function), which can be represented by the following formula:

$$\mu(x;a,b,c,d) = \begin{cases} 0\ dla\ x \le a \\ \dfrac{x-a}{b-a}\ dla\ a\ < x\ < b \\ 1\ dla\ b \le x \le c \\ \dfrac{d-x}{d-c}\ dla\ c < x < d \\ 0\ dla\ x\ \ge d \end{cases}$$

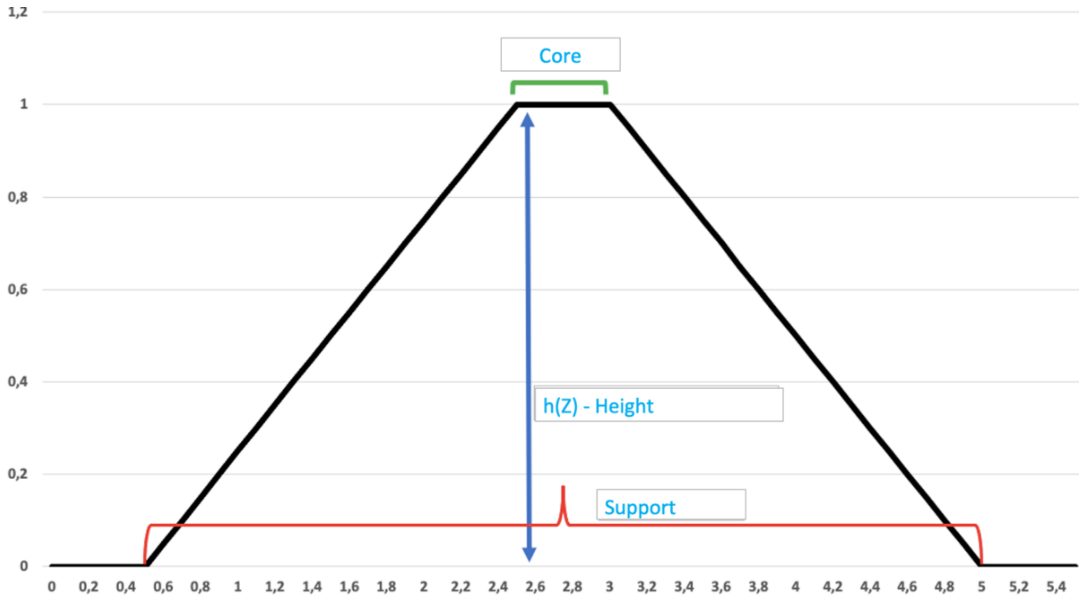
The design of the study involving fuzzy sets in decision making is as follows:

1) The first element of the study is to make forecasts with the use of 140 neural networks (three types of networks with different settings). In this way, 140 forecasts for a given day are obtained.
2) The selection of one forecast for a given day will be made on the basis of the membership function and the price on the day of making the investment decision.

In the empirical study, two membership functions were used - triangular and trapezoidal, and six methods of selecting a value for which the membership function equals 1. For a triangular number, this place may be:

- arithmetic mean,
- the median,
- mean without extreme values,
- median without extreme values
- Winsorized average of 25%
- and the Winsorized average covering 50% of forecast prices by all 140 neural networks.

FIGURE 1. GRAPHICAL REPRESENTATION OF A FUZZY SET



According to the formula presented above, the trapezoidal membership function is characterized by a range for which the membership function value is 1. In the empirical study for the trapezoidal membership function, the middle value of the range assuming membership is equal to 1 of the characteristics described above, i.e. mean, median, etc., and the span of this range is 10% of the difference between the highest and the lowest forecast price. On the other hand, the marginal values for the support of the set are the maximum and minimum forecast coming from 140 forecasts for a given day.

The purpose of this study is to make a decision to invest in growth or decline. In connection with this approach, the most important thing in the study is a binding decision on the forecast of a change in the exchange rate direction. Accordingly, two binding decisions are possible - increase or decrease. After creating the membership function from all forecasts, two scenarios are possible and each one has two sub-scenarios.

- Scenario A - for the price on the day of making the decision, the membership function takes the value equal to 0. It means that all forecasts (140 networks) indicate a price increase or decrease in relation to the day preceding the decision-making moment.
- Scenario B - for the price from the decision date, the membership function assumes a value different from 0.

In both scenarios, it is possible to make a decision to invest in both growth and decline. In scenario A, this decision depends on the position of the price on the axis - if the price on the day of making the decision is lower than the smallest value included in the carrier of a fuzzy number (resulting from a given membership function), a decision should be made to invest in growth, but if it is higher than the maximum value included in the carrier of a fuzzy number is a decision to invest in a decline. In scenario B, when the price on the decision-making date is "within" the carrier of the fuzzy number, the decisive factor is the area under the figure (if the figure on the left side of the carrier of the fuzzy number has a larger area, the binding decision is investment in decline, if on the right - growth). In order to illustrate all possible variants, the figure shows possible situations together with an indication of the decision made (in the example, a triangular membership function was used). In the examples, the green marker indicates the theoretical price on the day of making the decision (b) and the blue figure corresponds to the shape of a triangular membership function on the base ac, where a is the minimum forecast and c the maximum forecast.

The next stage assumes checking the accuracy of forecasts by comparing the decisions made in the described scheme with the actual directions of changes in exchange rates based on historical data.

FIGURE 2. FLOW CHART OF DECISION MAKING USING FUZZY LOGIC

For the two next graphs presented in Figure 2, the decision is made by means of the surface area, which is calculated as a definite integral from the membership function, the integration limits of which are the maximum (minimum) value of the forecast and the price on the day of making the decision. The analysis will present the impact on validity of changes in the shape of the membership function, as well as the method of assuming values for which the value of the membership function is 1.

In the study, the accuracy of forecasts using the method with fuzzy sets will be compared with two other methods that also use all 140 neural network forecasts on a given day.

The first of these is the majority decision (MD) method. The majority decision selection method is understood as a situation where the decision on the direction of change is made based on the following scheme:

- on day t_n prices are forecast at day t_{n+k},$gdzie\ k \in < 1{,}10 >$ using a total of 140 network settings - 49 for ELM and MLP and 42 LSTM,
- forecasts for each network type are compared with the price at day t_n,
- in this way, the predicted direction of change (increase, decrease or no change) is obtained,
- then the number of decisions corresponding to each direction of change within the neural network type is summed up,
- decision, which is considered a decision taken by a given type of neural network is equivalent to the decision, which in the previous point is characterized by the largest number.

The second method - the method of average accuracy of all networks (AA) - is to determine the accuracy of forecasts for all 140 settings of neural networks. And then calculating the average accuracy for the examined horizon and currency.

III. DATA DESCRIPTION

The empirical study considered three currency pairs - CHF/EUR, GBP/EUR, and USD/EUR. The exchange rate of the currency pairs was chosen in such a way that the quoted currency is always the euro, and the base currencies are CHF, GBP, and USD - such a rate informs how much euro one unit of the other three currencies can be bought for. The data from the three currency pairs are from 1.01.2015 to 31.12.2019. The data are divided into a learning set and a test set. The test is performed on price levels and logarithmic returns and the forecast horizon is between 1 and 10 days. The learning set is always a hundred days before the forecasting day, which means that the learning set always contains an equal number of observations, but their range depends on the forecasting day. For the returns of selected currency pairs basic characteristics were calculated, i.e., mean, deviation, skewness, and kurtosis. These characteristics are presented in Table 1.

TABLE 1. CHARACTERISTICS OF CURRENCY PAIRS

Currency pair	Arithmetic mean	Standard deviation	Skewness	Kurtosis
CHF/EUR	-0,00011	0,00492	0,07852	2,38802
GBP/EUR	-0,00007	0,00558	-1,26697	15,24767
USD/EUR	0,00006	0,00515	-0,02394	2,70457

Note: The characteristics were calculated for rates of return.

The skewness, when it takes a value close to 0, indicates no asymmetry of the results, above 0 indicates right-handed asymmetry of the distribution, and results below 0 indicate left-handed asymmetry of the distribution. The kurtosis results for all studied currency pairs indicate a leptokurtic distribution.

For all currency pairs, the KPSS test was conducted, whose null hypothesis is that the time series is stationary. The test resulted in the information that for all three currency pairs returns are characterized by stationarity.

IV. RESEARCH

The first element of the study was to compare the average results for each of the neural network settings with the decision selection method that was predicted by the majority of networks. Table 2 shows the collective results indicating the method that achieved better percent validity scores. The method in the table marked with MD is the method of most nets, while AA is the average validity of all nets.

TABLE 2. COMPARISON OF THE AVERAGE ACCURACY RESULTS OF NEURAL NETWORKS WITH THE FORECAST SELECTION METHOD FOR THE MAJORITY OF NETWORKS

Currency pair	Type of data	Type of NN	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
CHF/EUR	Price level	ELM	AA	AA	AA	MD	MD	MD	MD	AA	AA	AA
		MLP	AA	AA	AA	MD	AA	AA	AA	AA	AA	AA
		LSTM	AA	AA	AA	AA	AA	MD	MD	MD	AA	AA
	Returns	ELM	AA	AA	MD	AA	MD	MD	AA	MD	MD	MD
		MLP	AA	AA	AA	AA	MD	MD	MD	MD	MD	MD
		LSTM	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA
GBP/EUR	Price level	ELM	AA	AA	AA	AA	MD	MD	MD	MD	MD	MD
		MLP	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA
		LSTM	AA	AA	AA	AA	AA	AA	AA	AA	AA	AA
	Returns	ELM	AA	AA	AA	AA	AA	AA	MD	MD	MD	MD
		MLP	AA	AA	MD	MD	MD	MD	MD	MD	MD	MD
		LSTM	MD	AA	MD	AA	MD	MD	MD	MD	MD	MD
USD/EUR	Price level	ELM	AA	AA	AA	AA	MD	AA	MD	AA	AA	AA
		MLP	AA	AA	AA	MD	AA	MD	AA	AA	MD	AA
		LSTM	AA	AA	AA	AA	AA	AA	AA	AA	AA	MD
	Returns	ELM	AA	MD	MD	MD	MD	MD	MD	MD	MD	MD
		MLP	MD	AA	MD	MD	AA	AA	MD	AA	MD	AA
		LSTM	MD	AA	AA	MD	MD	AA	AA	AA	MD	AA

Taking into account the applied neural networks for a given currency (rows), it should be noted that for 18 cases the majority of networks was obtained 5 times in a given row and these cases always take place when the forecast is made on the rates of return for CHF / EUR in forecasts ELM and MLP networks, for GBP / EUR in forecasts with MLP and LSTM networks once for USD / EUR forecasted by ELM network. On the other hand, analyzing the forecast horizon (columns) for 10 cases, for two, better results were obtained by the method of the majority of networks for t + 7 and t + 9, and for t + 5 and t + 6, each method exceeded the other nine times, which proves a draw. However, it should be noted that when it comes to forecasting at price levels, there has never been a draw or advantage of the majority of the network's method. Table 3 shows the percentage differences between the methods listed, i.e. the average accuracy within a given type of network and the decision made by the majority of networks. Positive differences indicate an advantage of AA, negative an advantage of MD.

TABLE 3. COMPARISON OF THE PERCENTAGE DIFFERENCES BETWEEN THE METHOD OF AVERAGE ACCURACY RESULTS OF NEURAL NETWORKS AND THE METHOD OF SELECTING THE FORECAST WITH THE MAJORITY OF NETWORKS.

Currency pair	Type of data	Type of NN	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
CHF/EUR	Price level	ELM	1,1577%	0,3991%	0,1981%	-0,0425%	-0,1996%	-0,1557%	-0,2406%	0,1896%	0,0849%	0,3850%
		MLP	0,4670%	0,1161%	0,1925%	-0,2080%	0,0977%	0,3340%	0,1076%	0,0283%	0,1288%	0,2944%
		LSTM	0,2262%	0,3996%	1,7601%	1,4943%	1,3391%	-0,3484%	-0,1222%	-0,2989%	0,4689%	0,7116%
	Returns	ELM	0,0991%	0,0693%	-0,0991%	0,0991%	-0,0778%	-0,1189%	0,0396%	-0,1090%	-0,1316%	-0,2321%
		MLP	0,4133%	0,9780%	0,4585%	0,0835%	-0,0962%	-0,0920%	-0,2420%	-0,3128%	-0,4217%	-0,2448%
		LSTM	5,2440%	5,5677%	0,8355%	1,3539%	0,8718%	0,7199%	1,6165%	2,2323%	0,8553%	1,8130%
GBP/EUR	Price level	ELM	1,5044%	0,7289%	0,8704%	0,1359%	-0,1670%	-1,2737%	-0,6057%	-0,4685%	-0,3128%	-0,5916%
		MLP	1,1322%	1,3233%	1,0714%	1,1931%	1,7535%	2,2658%	1,0006%	0,9949%	0,6609%	0,7274%
		LSTM	0,8206%	1,4035%	1,8130%	2,4305%	1,7684%	2,0804%	0,5515%	0,7348%	0,5218%	0,9164%
	Returns	ELM	0,1231%	0,2590%	0,3892%	0,0892%	0,0906%	0,0354%	-0,0764%	-0,1543%	-0,3099%	-0,2675%
		MLP	0,7968%	0,1698%	-0,6496%	-0,1769%	-0,2378%	-0,8293%	-0,0156%	-1,1619%	-0,7558%	-0,3199%
		LSTM	-0,0611%	0,0066%	-0,0330%	0,0132%	-0,0380%	-0,0793%	-0,0132%	-0,0132%	-0,0578%	0,0000%
USD/EUR	Price level	ELM	0,3099%	0,1585%	0,2010%	0,5817%	-0,0849%	0,0821%	-0,0665%	0,4529%	0,3694%	0,1415%
		MLP	0,9638%	0,1755%	0,2505%	-0,0693%	0,1132%	-0,3581%	0,1514%	0,2052%	-0,1854%	0,1090%
		LSTM	1,0320%	1,3077%	0,8487%	0,9098%	1,3127%	0,0776%	0,6687%	0,1833%	0,2328%	-0,1073%
	Returns	ELM	0,0198%	-0,0609%	-0,0212%	-0,0410%	-0,1217%	-0,1401%	-0,1642%	-0,1783%	-0,1104%	-0,1599%
		MLP	-0,7458%	0,3637%	-0,8180%	-0,2038%	0,0637%	0,0340%	-0,1245%	0,0340%	-0,0184%	0,0269%
		LSTM	-0,0198%	0,4557%	0,5366%	-0,0231%	-0,0892%	0,0991%	0,0495%	0,0892%	-0,0099%	0,5961%

Note: The values in the table represent the percent difference between the Average Network Reliability and the Most Network Method. A positive value means that the average network validity achieved better results in a given case, while a negative value means that the method of the majority of networks had better results.

The preliminary study presented above is a reference point for the accuracy results that will be obtained by neural networks together with the method of selecting the final decision thanks to the use of fuzzy logic. In the last part of the article, the accuracy of these methods will be compared.

Table 4 presents the accuracy results obtained with all the above-described methods of generating a fuzzy number for the forecast MLP for currency pair USD / EUR Note: The column shows the accuracy of forecasts for various forecast horizons (from 1 to 10 days), distinguishing between the method of selecting the kernel of the set distinguished in the first column. The second column contains the symbols corresponding to the given methods.

For each of the networks and currency pairs, a table was prepared similar to the table above, which consists of 9 tables in total (combination of three types of neural networks and three currency pairs) illustrating the accuracy of the tested method with a distinction between the investment horizon and the method of selecting the kernel of the set. To ensure the clarity of the article, the tables below present the collective results of these 9 tables.

Table 5 presents the results of the study, which took into account the accuracy of the given method of selecting the kernel of the collection, using the symbols presented in Table 4.

TABLE 4. ACCURACY OF USD / EUR FORECASTS WITH MLP NEURAL NETWORK DUE TO THE WAY OF BUILDING A FUZZY NUMBER

Function type and selection of the core	Symbol	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Arithmetic mean trapezoidal function	&1	53,2964%	53,0882%	55,0313%	54,8926%	56,0029%	55,7253%	54,9619%	55,7947%	53,0883%	54,6149%
Median trapezoidal function	&2	53,2641%	53,1250%	55,0695%	54,9307%	56,0417%	55,6946%	54,9307%	55,7640%	53,0557%	54,5834%
Arithmetic mean without outliers trapezoidal function	&3	53,2316%	53,1619%	55,1077%	54,9688%	56,0112%	55,7332%	54,9688%	55,7333%	53,0925%	54,5520%
Median without outliers trapezoidal function	&4	53,1992%	53,1987%	55,1459%	54,9375%	55,9807%	55,7025%	54,9375%	55,7026%	53,0600%	54,5204%
Winsorized Mean 25% trapezoidal function	&5	53,2361%	53,2356%	55,1148%	54,9063%	55,9502%	55,6718%	54,9063%	55,7413%	53,0968%	54,5582%
Winsorized Mean 50% trapezoidal function	&6	53,2730%	53,2032%	55,0836%	54,8750%	55,9197%	55,6410%	54,8750%	55,7106%	53,0643%	54,5961%
Arithmetic mean triangular function	#1	54,2679%	54,6842%	55,0313%	56,9049%	57,1826%	56,7662%	58,7786%	56,6274%	53,4352%	54,2680%
Median triangular function	#2	54,2362%	54,6528%	55,0001%	56,8750%	57,1529%	56,8055%	58,8194%	56,6667%	53,4029%	54,2363%
Arithmetic mean without outliers triangular function	#3	54,2044%	54,6907%	54,9689%	56,8451%	57,1925%	56,8449%	58,8602%	56,7060%	53,3706%	54,2739%
Median without outliers triangular function	#4	54,2420%	54,6593%	54,9377%	56,8845%	57,2322%	56,8150%	58,8317%	56,6760%	53,4076%	54,3115%
Winsorized Mean 25% triangular function	#5	54,2103%	54,6278%	54,9758%	56,9240%	57,2719%	56,8544%	58,8725%	56,7153%	53,3753%	54,2798%
Winsorized Mean 50% triangular function	#6	54,1785%	54,6657%	55,0139%	56,9635%	57,2422%	56,8245%	58,8439%	56,6852%	53,4123%	54,2481%

TABLE 5 SUMMARY OF THE FUZZY NUMBER CONSTRUCTION METHOD WITH THE BEST ACCURACY FOR A GIVEN CURRENCY PAIR AND THE FORECAST HORIZON

Currency pair	Type of NN	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
CHF/EUR	ELM	#4	#1	#1	#6	#6	#6	#6	#6	#1	#4
	MLP	&3	#5	&4	#3	#3	#2	#1	#1	#3	&2
	LSTM	#4	#4	#1	#6	#6	#6	#5	#1	&5	#6
GBP/EUR	ELM	&4	&6	&6	&6	&6	&6	&6	&6	&4	&3
	MLP	&5	&4	&1	&1	&3	&3	&3	&3	&5	&5
	LSTM	&1	&2	&1	&1	&1	&2	&1	&1	&3	&1
USD/EUR	ELM	&1	#3	#1	&6	#6	#6	#6	#6	#1	#4
	MLP	#1	#3	&4	#6	#5	#5	#5	#5	#1	&1
	LSTM	&6	&2	&5	&1	&6	&1	&6	&2	&1	&4

Note: The symbols in the table indicate which method of selecting the kernel of the network obtained the highest accuracy for a given currency pair. The meaning of the symbols is as follows # denotes a triangular membership function while & the trapezoidal one. The numbers next to these symbols indicate the method of selecting the kernel of the set: 1 - arithmetic mean, 2 - median, 3 - arithmetic mean without extreme values, 4 - median without extreme values, 5 - Winsorized average rejecting 25% of observations, 6 - Winsorized mean rejecting 50 % of observations.

In order to summarize the results contained in Table 5, Table 6 has been prepared. Table 6 presents the ranking of the fuzzy number construction methods, depending on the number of cases of the most accurate forecasting for a given method. There are 90 variants in all (10 forecast horizons with three different neural networks for three currency pairs). The collective results indicate that the method based on the trapezoidal function turned out to be the best 48 times and the best method based on the triangular function 42 times. Within the individual types of membership functions, a 14-fold occurrence as the best method is the method based on the arithmetic mean and trapezoidal function and the Winsorized mean for 50% of the data and the triangular membership function. The next most common methods of selecting the kernel of a set (11 times) are the same two methods indicated above, but for different functions, i.e. arithmetic mean and triangular function, and 50%.Winsorized mean and trapezoidal function. This would indicate that the best method of selection is to use an arithmetic or Winsorized mean that covers half of the data regardless of the membership function. It should be noted in Table 6 that a total of as many as 69 out of 90 occurrences relate to the selection methods based on the arithmetic mean and both Winsorized means.

Tables 7 and 8 present the results of the extension of the study with validity for the average network validity and the validity of the method of selecting the majority of networks, i.e. the two methods discussed at the beginning of the chapter. The ranking of the methods from Table 7 is presented in Table 8. Table 7 shows 14 out of 29 cases in which the AA and MD methods obtained the best results, i.e. the average accuracy of all networks and the choice of the method of most networks, applies to the USD / EUR currency pair, of which as many as 8 are LSTM networks. The LSTM network for the USD / EUR currency pair achieves the best accuracy, which may translate into the difficulty of improving these results with other methods. The situation is different for the MLP network and the GBP / EUR currency pair, where for each forecast horizon better results were obtained by one of the methods taking into account the blurring. Based on this, it can be concluded that fuzzy methods obtain better relevance results for currencies with higher price fluctuations (this currency pair was characterized by high kurtosis). Although the best method, according to the ranking in Table 8, was the average accuracy of all networks. However, Table 8 can be considered more broadly, dividing the methods into three groups: mean validity of all networks (AA), decision-making method by the majority of networks (MD) and methods taking into account fuzzy sets (other). In this way, it can be seen that the AA and MD methods, i.e. the ones used for the benchmark, achieved the best validity in total for 29 out of 90 cases. For the remaining 61 variants, the methods taking into account fuzzy sets turned out to be better.

TABLE 6. SUMMARY OF THE NUMBER OF OCCURRENCES OF A GIVEN SELECTION OF THE METHOD OF CONSTRUCTING A FUZZY NUMBER

Function type and selection of the core	Symbol	Quantity as the best choice
Arithmetic mean trapezoidal function	&1	14
Median trapezoidal function	&2	5
Arithmetic mean without outliers trapezoidal function	&3	7
Median without outliers trapezoidal function	&4	6
Winsorized Mean 25% trapezoidal function	&5	5
Winsorized Mean 50% trapezoidal function	&6	11
Arithmetic mean triangular function	#1	11
Median triangular function	#2	1
Arithmetic mean without outliers triangular function	#3	5
Median without outliers triangular function	#4	5
Winsorized Mean 25% triangular function	#5	6
Winsorized Mean 50% triangular function	#6	14

TABLE 8. SUMMARY OF THE NUMBER OF METHODS FROM TABLE 7

Function type and selection of the core	Symbol	Quantity as the best choice
Arithmetic mean trapezoidal function	&1	8
Median trapezoidal function	&2	3
Arithmetic mean without outliers trapezoidal	&3	5
Median without outliers trapezoidal function	&4	4
Winsorized Mean 25% trapezoidal function	&5	3
Winsorized Mean 50% trapezoidal function	&6	8
Arithmetic mean triangular function	#1	7
Median triangular function	#2	1
Arithmetic mean without outliers triangular	#3	4
Median without outliers triangular function	#4	3
Winsorized Mean 25% triangular function	#5	5
Winsorized Mean 50% triangular function	#6	10
Mean accuracy of all settings	AA	23
Decision taken by a majority	MD	6

TABLE 7. LIST OF THE BEST ACCURACY METHODS FOR A GIVEN CURRENCY PAIR AND THE FORECAST HORIZON, TAKING INTO ACCOUNT THE ACCURACY FOR A NEURAL NETWORK EXTENDED WITH FUZZY LOGIC, AVERAGE ACCURACY OF NEURAL NETWORKS AND METHODS OF SELECTING THE MAJORITY OF NETWORKS

Currency pair	Type of NN	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
CHF/EUR	ELM	#4	#1	#1	#6	#6	MD	#6	#6	AA	AA
	MLP	AA	#5	&4	MD	#3	#2	#1	AA	#3	AA
	LSTM	#4	#4	#1	#6	AA	#6	#5	#1	AA	AA
GBP/EUR	ELM	AA	&6	&6	&6	&6	MD	&6	&6	&4	&3
	MLP	&5	&4	&1	&1	&3	&3	&3	&3	&5	&5
	LSTM	&1	&2	&1	&1	&1	&2	&1	AA	AA	AA
USD/EUR	ELM	&1	#3	#1	&6	#6	#6	#6	AA	AA	AA
	MLP	#1	#3	&4	#6	#5	MD	#5	#5	MD	AA
	LSTM	&6	&2	AA	AA	AA	AA	AA	AA	AA	MD

V. DISCUSSION

The results of conducted research confirm the effectiveness of neural networks in forecasting the direction of changes in currency pairs. One should agree with the statements cited in the introduction about the difficulties and complexity of forecasting in this market and many factors that may affect the increase or decrease in the accuracy of forecasts. The results of the empirical study indicated the possibility of improving the accuracy results of neural networks through the use of fuzzy logic. An additional advantage of the presented method is the fact that one final decision is selected out of 140 forecasts made with the use of neural networks with different settings. The same is true for the majority network selection method. The method with fuzzy sets turned out to be significantly better than the method of most networks. When comparing the results to the average network accuracy, it is necessary to take into account the fact that this average is calculated from 140 forecasts of different networks and with different settings, which means that in this set there are accuracies with high as well as lower results. However, in the case of transferring the average network validity method to practical ground, investments should be made in accordance with all 140 networks in order to obtain such a share of correct decisions, while in the case of the fuzzy set method, only 1 investment should be made. Therefore, it is necessary to point out not only the better results of the neural-fuzzy approach, but also the ease of its application in practice.

VI. CONCLUSIONS

The motivation for the study was the extensive use of neural networks and neural networks combined with fuzzy sets in forecasting in financial markets. Data from the foreign exchange market was selected for the study due to the high significance of exchange rate movements on the economies of countries. The aim of the study was to present a different approach to incorporate fuzzy sets in forecasting changes in foreign exchange markets using neural networks. Due to the importance of exchange rate changes for both practitioners and researchers, the methods are compared for their accuracy and ease of transfer to practical application. As a result of the empirical research, the strengths of the presented method are pointed out and it is proven that it can produce better accuracy results than other methods used. It was also observed that the method performs very well in situations of uncertainty and dynamic market changes, by obtaining better forecast accuracy for currencies with high kurtosis. The study was carried out for a number of different neural network settings and types (140 in total) and three basic currency pairs. This study provides an indication of the applicability of this method and can be extended to other markets and other less basic currency pairs

VII. References

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