Chapter 11
Detecting Nasdaq Composite Index Trends with OFNs

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Abstract The chapter presents a novel way of describing changes in the stock index and the identification of potential trends. The authors already used a similar approach to describe the stock exchange index [16]; this chapter is a continuation and another application of work on this issue. The method for detecting patterns in a trend by means of linguistic variables is described. The use of computational operations on numbers in the Ordered Fuzzy Number (OFN) notation [40–42] enables us to set the values of linguistic variables and thus conduct fuzzification of the input. By using one OFN number it is possible to store five parameters of index quotations (open, high, low, and close values as well as a change direction). The OFN numbers are conveyed into a linguistic form. In order to find trend sequence similarity the following applies: sequence identity with the input frame expressed as a percentage, frame size, the level of threshold conformity with the frame (threshold), and how often the pattern is present (frequency). A dedicated computer program to detect patterns is implemented. The program used data from the index Nasdaq Composite from the years 2006-2016. The results represent a further step to develop effective methods of rule-based forecasting.

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11.1 Introduction

In comparison to existing methods, more accurate forecasting methods can be obtained using a rule-based forecasting (RBF), a technique combining data extrapolation [7, 13, 14, 25, 26, 43–45], time series [28, 29, 44, 45], and elements of expert systems [5–7, 22, 23, 34, 37, 46]. The four most important methods of extrapolation were used: linear regression, random walk, and Brown's exponential smoothing, as well as Holt's exponential smoothing. In order to create rules some information from the literature, surveys, and knowledge of several experts was adapted [17, 19–21, 36, 38, 39]. The rules were calibrated using 80 time series. In contrast, the validation needed another 40 series. In the opinion of the authors, RBF has been successfully applied by combining domain expertise with statistical methods. This has been confirmed by many studies in the recent literature, where rule-based forecasting is a fast-growing technology. It is worth mentioning a few examples from a very comprehensive literature such as M. Adya, J.S. Armstrong, and F. Collopy [1–3, 8, 9], who publish in the International Journal of Forecasting, a magazine that inspires other authors associated with the RBF methods. In this chapter time series of index data were preliminarily fuzzified [30, 33] to check the proposed methods of detecting trends [18]. Trends identified in the sequence of literals are then used to develop trend prediction rules. Therefore fuzzy logic [12, 13, 16, 35] was used to develop linguistic data input. Data for the study were quotations of the Nasdaq Composite index from the years 2006–2016. Figure 11.1 shows the data in an illustrative manner. Table 11.1 contains Nasdaq index data for a single trading day. Daily data are: opening, maximum, minimum, and closing values as well as the percentage change

Fig. 11.1 NASDAQ Composite index quotations from 2006 to 2016

Table 11.1 Selected historical NASDAQ Composite index. The dataset covers the time period from November 1, 2016 to November 30, 2016

Index	Date	Open	High	Low	Close	Change
W	Nov 30, 2016	5391.35	5393.15	5323.68	5323.68	-1.26%
U	Nov 29, 2016	5370.98	5403.86	5360.56	5379.92	0.17%
T	Nov 28, 2016	5387.92	5396.27	5364.91	5368.81	-0.35%
S	Nov 25, 2016	5388.49	5398.92	5379.28	5398.92	0.19%
R	Nov 23, 2016	5366.55	5380.68	5350.68	5380.68	0.26%
P	Nov 22, 2016	5384.75	5392.26	5365.60	5386.35	0.03%
O	Nov 21, 2016	5336.78	5369.83	5334.16	5368.86	0.60%
N	Nov 18, 2016	5340.97	5346.80	5315.53	5321.51	-0.36%
M	Nov 17, 2016	5295.07	5334.05	5288.16	5333.97	0.73%
L	Nov 16, 2016	5253.73	5299.63	5251.88	5294.58	0.78%
K	Nov 15, 2016	5241.35	5287.06	5236.25	5275.62	0.65%
J	Nov 14, 2016	5246.33	5247.17	5192.05	5218.40	-0.53%
I	Nov 11, 2016	5191.82	5241.08	5179.64	5237.11	0.87%
H	Nov 10, 2016	5283.48	5302.68	5145.32	5208.80	-1.41%
G	Nov 09, 2016	5143.86	5258.99	5143.86	5251.07	2.08%
F	Nov 08, 2016	5154.99	5214.17	5145.30	5193.49	0.75%
E	Nov 07, 2016	5128.99	5169.41	5122.77	5166.17	0.72%
D	Nov 04, 2016	5034.41	5087.51	5034.41	5046.37	0.24%
C	Nov 03, 2016	5104.70	5115.06	5053.52	5058.41	-0.91%
B	Nov 02, 2016	5147.27	5156.70	5097.56	5105.57	-0.81%
A	Nov 01, 2016	5199.77	5201.13	5112.32	5153.58	-0.89%

as compared to the day before. These five values are replaced by the linguistic values. Table 11.1 shows both the linguistic values and index quotations.

11.2 Application of OFN Notation for the Fuzzy Observation of NASDAQ Composite

Data from November this year for the NASDAQ Composite are presented in Table 11.1. Quotations are given in a widely used format for this type of time series. Subsequent letters of the alphabet represent values for consecutive trading days. Figure 11.2 shows an OHLC (open, high, low, close) chart of the Nasdaq Composite index for one month. The graph shows the following attributes for each of the daily quotations: opening, closing, highest, and lowest value. These attributes, along with the change parameter are shown in Table 11.1. In addition, decrease in quotation is

Fig. 11.2 Nasdaq Composite OHLC chart for the period of November 1, 2016 to November 30, 2016 (based on www.stockcharts.com).

Table 11.2 Characteristic points

Ordered OFN number	f_0	f_1	g_1	g_0	OFN number orientation
Nasdaq Composite Index	Open	High	Low	Close	Change

marked in red and increase is marked in black. Positions **A**, **B**, and **C** in Fig. 11.2 show a decrease in quotations on specified days. Another four quotations-**D**, **E**, **F**, **G**-show an increase in the value of the Nasdaq Composite. A very large spread between the minimum and maximum value, and between the opening and closing are on **H**; these are decreasing quotations. This is followed by increases to date **S** with only two days of drops (**J** and **N**) in the range. Point **P** is interesting, because the opening value is virtually level with the closing value, despite some fluctuations of the Nasdaq Composite value during the trading day. It is essential that **P** be located near the top of the local peak. Then visualizations **T** and **W** demonstrate declines from the local peak. As the chart above may not be unambiguous in terms of the trend interpretation the authors introduce the logic of Ordered Fuzzy Numbers [14, 24, 30] in order to interpret the quotations. Table 11.2 shows the OFN characteristic points with the Nasdaq Composite quotation parameters as listed in Table 11.2.

Figure 11.4 is an OHLC chart with Nasdaq index parameters. In the considered single day there has been an increase in quotations. The translation of data from Fig. 11.4 on the OFN is presented in Table 11.3. The resulting fuzzy number is interpreted graphically in Fig. 11.3. The arrow of fuzzy numbers is directed towards

Table 11.3 Example of positively directed OFN number for the Nasdaq index

OFN number	$f_{(0)}$	$f_{(1)}$	$g_{(1)}$	$g_{(0)}$	OFN number positive orientation
Nasdaq Composite Index	Open	High	Low	Close	Change (positive value)

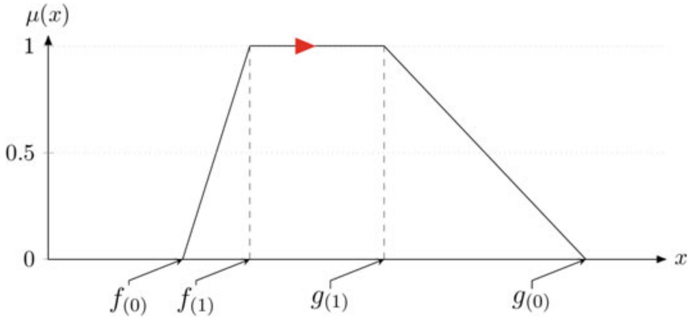

Fig. 11.3 Graphically displayed positively directed OFN number and its characteristic points as used for the Nasdaq Composite

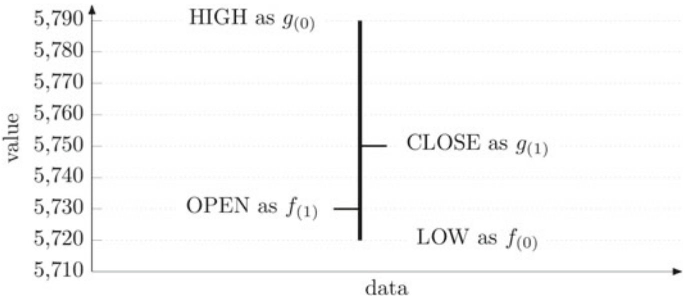

Fig. 11.4 Graphically displayed change parameter positive value as used in the Nasdaq Composite OHLC chart

increasing values symbolizing the positive direction of the OFN and reflecting an increase in the quotations.

Figure 11.5 shows the fuzzy number stretched on the same values as in Fig. 11.3. However, the direction of the OFN here is the opposite. Chart 2.6 depicts the decrease in quotations for a single day of trading. It should be noted that the equivalent of the index's downward movement is a negative direction of the OFN (Fig. 11.6).

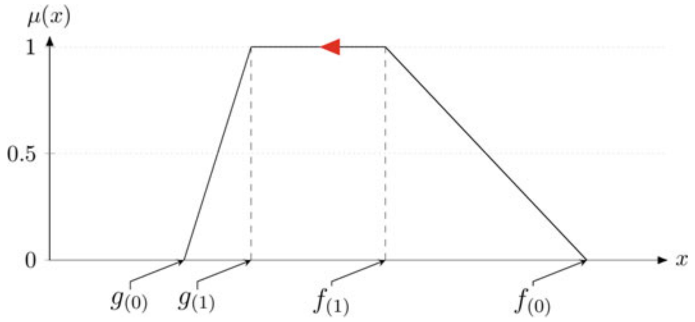

Fig. 11.5 Graphically displayed negatively directed OFN and its characteristic points as used for the Nasdaq Composite

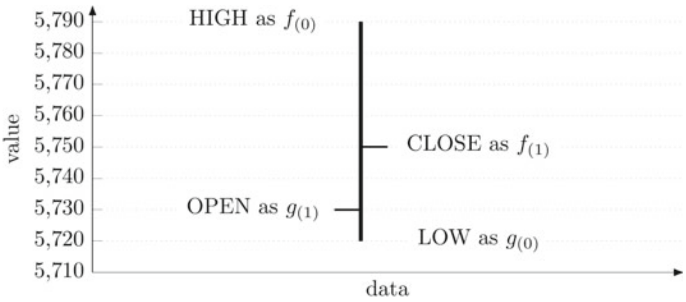

Fig. 11.6 Graphically displayed change parameter negative value as used in the Nasdaq Composite OHLC chart

11.3 Ordered Fuzzy Number Formulas

Nasdaq Composite index values $R_1 \div R_m$ relate to a single trading day. Fuzzy observation in OFN notation is performed on a set of R. The observation is for one dependent and four independent attributes. For each day the number $\mathbb{R}_i \in \{R_1 \div R_m\}$ is created of the four required values. Symbols of time are, respectively, t_i, the day of the measurement, whereas $t_{OPEN}, t_{MIN}, t_{tMAX}$ i t_{CLOSE} are, respectively, quotations of opening, minimum, maximum, and close value (Table 11.4).

Definition 1 On a given day t_i, the set forming fuzzy observation of the Nasdaq Composite index, is provided as

$$\mathbb{R}/t_i \in \{\mathbb{R}^{(0)}/t_{OPEN},\ \mathbb{R}^{(1)}/t_{MIN},\ \mathbb{R}^{(1)}/t_{MAX},\ \mathbb{R}^{(0)}/t_{CLOSE}\} \tag{11.1}$$

where

$$t_{CLOSE} > \{t_{MIN}, t_{MAX}\} > t_{OPEN}$$

$$f_{\mathbb{R}}(0) < f_{\mathbb{R}}(1) < g_{\mathbb{R}}(1) < g_{\mathbb{R}}(0)$$

Table 11.4 Example of a negatively ordered OFN as an interpretation of the Nasdaq index

OFN	$f_{(0)}$	$f_{(1)}$	$g_{(1)}$	$g_{(0)}$	OFN positive orientation
Nasdaq Composite Index	Open	High	Low	Close	Change (negative value)

The OFN arrangement (order) is synonymous with the measurement time of t movement intensity, where $t \in \{t_{OPEN}, t_{MIN}, t_{tMAX}, t_{CLOSE}\}$. The measurements must be performed in a specific order. The OFN order in Fig. 11.3 is the direction of index changes for one trading day. The default direction of OFN $\mathbb{R}$ is positive (Fig. 11.2).

Lemma 1

$$\mathbb{R}_{positive} = \begin{cases} \mathbb{R}_{CLOSE} \leq \mathbb{R}_{OPEN} \\ \mathbb{R}_{OPEN}, \mathbb{R}_{MIN}, \mathbb{R}_{MAX}, \mathbb{R}_{CLOSE} \\ f_{\mathbb{R}}(0), f_{\mathbb{R}}(1), g_{\mathbb{R}}(1), g_{\mathbb{R}}(0) \end{cases} \tag{11.2}$$

and the opposite case is

$$\mathbb{R}_{negative} = \begin{cases} \mathbb{R}_{CLOSE} > \mathbb{R}_{OPEN} \\ \mathbb{R}_{CLOSE}, \mathbb{R}_{MAX}, \mathbb{R}_{MIN}, \mathbb{R}_{OPEN} \\ f_{\mathbb{R}}(0), f_{\mathbb{R}}(1), g_{\mathbb{R}}(1), g_{\mathbb{R}}(0) \end{cases} \tag{11.3}$$

The NASDAQ was launched in the 1970 s and was the first fully electronic securities trading system in the world. The stock market traded shares of companies mainly related to modern technology (IT). The Nasdaq Composite is one of the three major US indices, next to the Dow Jones Average and the S&P500 [47–50]. As for 2016, listed on the NASDAQ are approximately 3,000 companies, including Apple, Google, Microsoft, and Intel. The Nasdaq composite index is an aggregate of the common stocks listed on the NASDAQ stock market. The formula for aggregating fuzzy observation of subaggregate S_m for n component companies of the index is as follows.

Definition 2 Fuzzy observation of index Nasdaq Composite at the time t_i is a set of

$$s_m = \sum_{i=1}^{n} \begin{pmatrix} \mathbb{R}_{positive} & \mathbb{R}_{negative} \\ \mathbb{R} \cdot w_i & \mid -\mathbb{R} \cdot w_i \end{pmatrix} \tag{11.4}$$

where $n \leq 3000$ and $w_i \in \{w_1, \ldots w_n\}$ is a vector of the individual companies' impact, default $w_i = 1$.

The weight of each company in the index is

$$P_j = \frac{\mathbb{R}_j * w_j}{\sum_{i=1}^{m} \mathbb{R}_i * w_i} * 100\% \tag{11.5}$$

where $j \in [1, m]$

Definition 3 If a subaggregate *Sm* of the Nasdaq Composite aggregate with a certain number n of (e.g., sector-related) companies has a different direction of the OFN from the direction of the main index, then it can be assumed that it is a predictor of trend change. This includes the rule:

$$\begin{aligned} \textbf{IF } NasdaqComposite\ is\ positive\ \textbf{AND } S_m\ is\ negative \\ \textbf{THEN } Possible\ change\ is\ true \end{aligned} \tag{11.6}$$

11.4 Conclusions

Investing in the stock market is associated with high risk. This is due to the lack of ideal solutions for the analysis of market data and predictions in short- and long-term changes in indices, major stock market indicators. Processes occurring on the stock markets have nonlinear chaotic characteristics, making it difficult to study them. The technical analysis often uses expert knowledge and expert rules to detect and use recognizable trends [43]. One can base investment strategy on trends that will bring profits during the boom and limit losses when a market is in decline. Expert knowledge and rules can be transferred to digital form. Currently, there are many methods for identifying trends on the stock exchange [16, 50]. Many of them are unattractive due to their complicated structure. An interesting alternative to describing the phenomenon of the trend is the application of fuzzy numbers and fuzzy logic [4, 10, 11, 31, 32]. The chapter presents Ordered Fuzzy Numbers, which use five specific index parameters as well as index analysis methods to identify the occurrence of a trend. Ordered Fuzzy Number notation made it possible to replace up to five attributes (open, close, high, low, change) describing the index quotes with a single OFN. In addition, the use of OFNs lets one quickly detect changes in the trend, which is very important in short-term investments. The authors previously proposed similar solutions based on research WIG20 [16]; there are also other works on similar solutions and financial investment [27, 28]. The authors intend to carry out further research in this area in order to find more versatile and accurate prediction models to identify market trends.

References

1. Adya, M.: Corrections to rule-based forecasting: findings from a replication. Int. J. Forecast. **16**(1), 125–127 (2000). http://www.sciencedirect.com/science/article/pii/S0169207099000345
2. Adya, M., Armstrong, J.S., Collopy, F., Kennedy, M.: An application of rule-based forecasting to a situation lacking domain knowledge. Int. J. Forecast. **16**(4), 477–484 (2000)
3. Adya, M., Collopy, F., Armstrong, J.S., Kennedy, M.: Automatic identification of time series features for rule-based forecasting. Int. J. Forecast. **17**(2), 143–157 (2001)

4. Angryk, R.A., Czerniak, J.: Heuristic algorithm for interpretation of multi-valued attributes in similarity-based fuzzy relational databases. Int. J. Approx. Reason. **51**(8), 895–911 (2010)
5. Apiecionek, L., Czerniak, J.M.: Qos solution for network resource protection. INFORMATICS 2013: PROCEEDINGS OF THE TWELFTH INTERNATIONAL CONFERENCE ON INFORMATICS pp. 73–76 (2013)
6. Apiecionek, L., Czerniak, J.M., Dobrosielski, W.T.: Quality of services method as a ddos protection tool. Intelligent Systems 2014, vol 2: Tools, Architectures, Systems, Applications **323**, 225–234 (2015)
7. Apiecionek, L., Czerniak, J.M., Zarzycki, H.: Protection tool for distributed denial of services attack. Beyond databases, architectures and structures, BDAS 2014 **424**, 405–414 (2014)
8. Armstrong, J.S.: Findings from evidence-based forecasting: Methods for reducing forecast error. Int. J. Forecast. **22**(3), 583–598 (2006)
9. Armstrong, J.S., Adya, M., Collopy, F.: Rule-based forecasting: Using judgment in time-series extrapolation. In: Principles of Forecasting, pp. 259–282. Springer, Berlin(2001)
10. Czabanski, R., Jezewski, J., Horoba, K., Jezewski, M.: Fetal state assessment using fuzzy analysis of fetal heart rate signals – agreement with the neonatal outcome. Biocybern. Biomed. Eng. **33**(3), 145–155 (2013)
11. Czabanski, R., Jezewski, M., Horoba, K., Jezewski, J., Leski, J.: Fuzzy analysis of delivery outcome attributes for improving the automated fetal state assessment. Appl. Artif. Intell. **30**(6), 556–571 (2016)
12. Czerniak, J., Zarzycki, H.: Application of rough sets in the presumptive diagnosis of urinary system diseases. Artif. Intell. Secur. Comput. Syst. **752**, 41–51 (2003)
13. Czerniak, J.: Evolutionary approach to data discretization for rough sets theory. Fundam. Inform. **92**(1–2), 43–61 (2009)
14. Czerniak, J.M., Apiecionek, Ł., Zarzycki, H.: Application of ordered fuzzy numbers in a new ofnant algorithm based on ant colony optimization. Beyond databases, architectures and structures, BDAS **(424)**, 259–270 (2014)
15. Czerniak, J.M., Dobrosielski, W., Zarzycki, H., Apiecionek, L.: A proposal of the new owlant method for determining the distance between terms in ontology. Intelligent Systems 2014, vol 2: Tools, architectures, systems, applications **323**, 235–246 (2015)
16. Czerniak, J.M., Zarzycki, H., Dobrosielski, W.T., Szczepański, J.: Application of ofn notation in the fuzzy observation of wig20 index trend for the period 2008-2016. In: Proceedings of the Fifteenth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets, Advances in Intelligent Systems and Computing. Springer, Berlin (2017)
17. Czerniak, J., Apiecionek, Ł., Zarzycki, H., Ewald, D.: Proposed caeva simulation method for evacuation of people from a buildings on fire. Adv. Intell. Syst. Comput. **401**, 315–326 (2016)
18. Czerniak, J., Dobrosielski, W., Apiecionek, L.: Representation of a trend in ofn during fuzzy observance of the water level from the crisis control center. Proceedings of the Federated Conference on Computer Science and Information Systems, IEEE Digital Library, ACSIS **5**, 443–447 (2015)
19. Czerniak, J.M., Zarzycki, H., Ewald, D.: AAO as a new strategy in modeling and simulation of constructional problems optimization. Simulation Modelling Practice and Theory, vol 76C, pp. 22–33. Elsevier (2017). https://doi.org/10.1016/j.simpat.2017.04.001
20. Czerniak, J.M., Zarzycki, H.: Artificial Acari optimization as a new strategy for Global Optimization of Multimodal Functions. J. Comput. Sci. Elsevier (2017). http://doi.org/10.1016/j.jocs.2017.05.028
21. Ewald, D., Czerniak, J.M., Zarzycki, H.: Approach to solve a criteria problem of the abc algorithm used to the wbdp multicriteria optimization. Intelligent systems 2014, vol 1: Mathematical foundations, theory, analyses **322**, 129–137 (2015)
22. Jezewski, M., Czabanski, R., Horoba, K., Leski, J.: Clustering with pairs of prototypes to support automated assessment of the fetal state. Appl. Artif. Int. **30**(6), 572–589 (2016)
23. Jezewski, M., Leski, J.M., Czabanski, R.: Classification Based on Incremental Fuzzy $(1 + p)$-Means Clustering, pp. 563–572. Springer International Publishing, Cham (2016)

24. Kacprzak, M., Kosiński, W.: On lattice structure and implications on ordered fuzzy numbers. In: Proceedings of the EUSFLAT. Artificial Intelligence and Soft Computing, vol. 7267 of LNCS, pp. 247–255 (2011)
25. Kacprzak, M., Starosta, B., Węgrzyn-Wolska, K.: Metasets and opinion mining in new decision support system. In: Rutkowski, L., Korytkowski, M., Scherer, R., Tadeusiewicz, R., Zadeh, L.A., Zurada, J.M. (eds.) Artificial Intelligence and Soft Computing, Part II. Lecture Notes in Artificial Intelligence, vol. 9120, pp. 625–636. Springer International Publishing (2015)
26. Kacprzak, M., Starosta, B., Węgrzyn-Wolska, K.: New approach to decision making. In: Abraham, A., Wegrzyn-Wolska, K., Hassanien, A.E., Snasel, V., Alimi, A.M. (eds.) Proceedings of the Second International Afro-European Conference for Industrial Advancement AECIA 2015. Advances in Intelligent Systems and Computing, vol. 427, pp. 397–407. Springer International Publishing (2015)
27. Kacprzyk, J., Wilbik, A.: Using fuzzy linguistic summaries for the comparison of time series: an application to the analysis of investment fund quotations. In: IFSA/EUSFLAT Conference pp. 1321–1326 (2009)
28. Kacprzyk, J., Wilbik, A., Zadrożny, S.: Linguistic summarization of time series using a fuzzy quantifier driven aggregation. Fuzzy Sets Syst. **159**(12), 1485–1499 (2008)
29. Kacprzyk, J., Wilbik, A., Zadrożny, S.: On some types of linguistic summaries of time series. In: Intelligent Systems, 2006 3rd International IEEE Conference on pp. 373–378. IEEE (2006)
30. Kosiński, W., Prokopowicz, P., Rosa, A.: Defuzzification functionals of ordered fuzzy numbers. Fuzzy Syst. IEEE Transactions on **21**(6), 1163–1169 (Dec 2013). doi:10.1109/TFUZZ.2013.2243456
31. Kosinski, W., Prokopowicz, P., Slezak, D.: Fuzzy reals with algebraic operations: Algorithmic approach. Intelligent Information Systems 2002, Proceedings pp. 311–320 (2002)
32. Kosinski, W., Prokopowicz, P., Slezak, D.: Calculus with fuzzy numbers. In: Bolc, L., Michalewicz, Z., Nishida, T (ed.) Intelligent Media Technology For Communicative Intelligence. Lecture Notes in Artificial Intelligence, vol. 3490, pp. 21–28 (2004), 2nd Intenational Workshop on Intelligent Media Technology for Communicative Intelligence, Warsaw, POLAND, SEP 13–14, 2004
33. Kosinski, W., Prokopowicz, P.: Fuzziness - Representation of Dynamic Changes ? In: Stepnicka, M., Novak, V., Bodenhofer, U (ed.) New Dimensions In Fuzzy LOGIC AND RELATED TECHNOLOGIES, VOL I, PROCEEDINGS. pp. 449–456. European Soc Fuzzy Log & Technol, UNIV OSTRAVA, OSTRAVSKA UNIV & OSTRAVE, DVORAKOVA 7, OSTRAVA 1, 701 03, CZECH REPUBLIC (2007), 5th Conference of the European-Society-for-Fuzzy-Logic-and-Technology, Ostrava, CZECH REPUBLIC, Sep 11–14, 2007
34. Kosiński, W., Prokopowicz, P., Ślęzak, D.: Neural Networks and Soft Computing: Proceedings of the Sixth International Conference on Neural Networks and Soft Computing, Zakopane, Poland, June 11–15, 2002, chap. On Algebraic Operations on Fuzzy Reals, pp. 54–61. Physica-Verlag HD, Heidelberg (2003). doi:10.1007/978-3-7908-1902-1_8
35. Leski, J.M.: Neuro-fuzzy system with learning tolerant to imprecision. Fuzzy Sets Syst. **138**(2), 427–439 (2003)
36. Leski, J.M.: On support vector regression machines with linguistic interpretation of the kernel matrix. Fuzzy Sets Syst. **157**(8), 1092–1113 (2006)
37. Mikolajewska, E., Mikolajewski, D.: Exoskeletons in neurological diseases - current and potential future applications. Adv. Clin. Exp. Med. **20**(2), 227–233 (2011)
38. Prokopowicz, P.: Methods based on ordered fuzzy numbers used in fuzzy control. In: Proceedings of the Fifth International Workshop on Robot Motion and Control, 2005. RoMoCo ’05. pp. 349–354 (June 2005). doi:10.1109/ROMOCO.2005.201448
39. Prokopowicz, P.: Adaptation of rules in the fuzzy control system using the arithmetic of ordered fuzzy numbers. In: Rutkowski, L., Tadeusiewicz, R., Zadeh, L., Zurada, J. (eds.) Artificial Intelligence and Soft Computing - ICAISC 2008, Lecture Notes in Computer Science, vol. 5097, pp. 306–316. Springer Berlin Heidelberg (2008). doi:10.1007/978-3-540-69731-2_30
40. Prokopowicz, P.: Flexible and simple methods of calculations on fuzzy numbers with the ordered fuzzy numbers model. In: Rutkowski, L., Korytkowski, M., Scherer, R., Tadeusiewicz,

R., Zadeh, L., Zurada, J. (eds.) Artificial Intelligence and Soft Computing, Lecture Notes in Computer Science, vol. 7894, pp. 365–375. Springer Berlin Heidelberg (2013). doi:10.1007/978-3-642-38658-9_33
41. Prokopowicz, P.: Analysis of the changes in processes using the kosinski's fuzzy numbers. In: Ganzha, M., Maciaszek, L., Paprzycki, M. (eds.) Proceedings of the 2016 Federated Conference on Computer Science and Information Systems. Annals of Computer Science and Information Systems, vol. 8, pp. 121–128. IEEE (2016). doi:10.15439/2016F140
42. Prokopowicz, P.: Proceedings of the Second International Afro-European Conference for Industrial Advancement AECIA 2015, chap. The Directed Inference for the Kosinski's Fuzzy Number Model, pp. 493–503. Springer International Publishing, Cham (2016). doi:10.1007/978-3-319-29504-6_46
43. Sobol, I., Kacprzak, D., Kosiński, W.: Optimizing of a company's cost under fuzzy data and optimal orders under dynamic conditions. Optimum. Studia Ekonomiczne **5**, 172–187 (2014)
44. Wei, L., Keogh, E.: Semi-supervised time series classification. In: Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining. pp. 748–753. ACM (2006)
45. Xi, X., Keogh, E., Shelton, C., Wei, L., Ratanamahatana, C.A.: Fast time series classification using numerosity reduction. In: Proceedings of the 23rd International Conference On Machine Learning. pp. 1033–1040. ACM (2006)
46. Zadrożny, S., Kacprzyk, J.: On the use of linguistic summaries for text categorization. In: Proceedings of IPMU. pp. 1373–1380 (2004)
47. Zarzycki, H.: Computer system for the evaluation of options contracts with monte carlo approach, (in polish). In: Studies and Proceedings of Polish association for Knowledge Management **22**, 226–233 (Bydgoszcz 2009)
48. Zarzycki, H.: Application of the finite difference cn method to value derivatives. In: Studies and Proceedings of Polish association for Knowledge Management **(42)**, 267–277 (Bydgoszcz 2011)
49. Zarzycki, H.: Modern technologies as a chance for options markets development, (in polish). In: National Scientific Conference Financial markets in electronic space (Kulice 2003)
50. Zarzycki, H.: Index arbitrage on the warsaw stock exchange, (in polish). VII Technical University of Szcszecin Computer Science Department Symposium (Szczecin 2003)