www.sjm06.com

Serbian Journal of Management 17 (1) (2022) 207 - 218

Serbian Journal of Management

DECISION MAKING REFLECTING THE FRACTALIZATION OF THE SOCIETY

Jan Kalina[a,b*]

[a]*The Czech Academy of Sciences, Institute of Computer Science, Pod Vodárenskou věží 2, 182 07 Prague 8, Czech Republic*
[b]*Charles University, Faculty of Mathematics and Physics, Sokolovská 83, 186 75 Prague 8, Czech Republic*

(Received 19 March 2021; accepted 01 March 2022)

Abstract

Although the mainstream economic doctrine relies on the concept of equilibrium, the current society has been recently facing serious challenges. While we can experience a gradually rise of the ideals of the knowledge society, we hold the opinion that the society (and the economies worldwide as well) will have a fractal structure following models investigated by the chaos theory. This paper is focused on decision making especially in economic or managerial tasks and its transforms due to the paradigm shift towards a fractal society in disequilibrium economic conditions. Statistical and information-theoretical aspects of decision support are discussed and a decision making example from the field of credit risk management is analyzed and presented.

Keywords: decision support, economic equilibrium, management, credit risk, information theory, chaos theory

1. INTRODUCTION

The current society has to face serious challenges because of the economic recession due to the COVID-19 pandemic, cultural changes, or disruptive climatic changes. Other events with hardly predictable economic consequences include globalization, negative interest rates, high noise level in capital markets (Klioutchnikov et al., 2017), uncertain (indecisive, unstable) economic policy (Liu et al., 2017), or far-reaching economic shocks after military operations (as in Ukraine in February 2022). On the other hand, unambiguously positive events such as increase of innovations, omnipresent digitalization, or availability of Big Data in various fields contribute to a

* *Corresponding author: kalina@cs.cas.cz*

DOI: 10.5937/sjm17-31413

gradual shift towards the ideals of knowledge society. Still, we hold the opinion that the future (knowledge) society will have a fractal structure following models investigated by the chaos theory.

From the economic point of view, the mainstream economic theory is based on the concept of general economic equilibrium. However, we can perceive the economies throughout the world to apparently diverge from the ideals of equilibrium to a state described as disequilibrium, insecurity, uncertainty, or confusion. The economies worldwide were considered already before the COVID-19 pandemic as turbulent, fractal-structured, or chaotic (Faggini et al., 2019). Of course, such unstable conditions negatively influence complex decision making tasks of economists, managers, or politicians. At the same time, the complexity (dimensionality) of economic systems increases as well together with their increasing vulnerability (sensitivity, non-robustness).

This paper is focused on decision making in economic or managerial context in a society which is rapidly changing. Naturally, decision making should undergo adequate transforms as well (Moreno-Jiménez & Vargas, 2018). Particularly, Section 2 discusses the concept of economic equilibrium and Section 3 presents recent economy transforms from the point of view of fractal theory. The rather limited human decision making has not been adapted by any evolution to the conditions of a fractal society, as explained in Section 4. Therefore, decision support systems can be considered as very perspective tools; they are discussed in Section 5. Section 6 presents an example from the field of credit risk management. Section 7 brings conclusions.

2. THE CONCEPT OF ECONOMIC EQUILIBRIUM AND ITS CRITIQUE

This section presents a discussion of the concept of equilibrium, which traditionally represents a popular concept in the economic theory. This chronologically presented overview pays attention to important milestones, which influenced the mainstream economic doctrine, including Nash equilibrium theory or the general economic equilibrium.

Equilibrium appears in various phenomena in the nature around us and thus naturally aroused the interest of philosophers and scientists in various disciplines. Already in the work of the Czech polyhistor John Amos Comenius (1592–1670), the central idea of harmony or panharmony corresponds to a (holistic) equilibrium of the nature, which may be perceived as an organic being. The economic understanding of an equilibrium has been many times recalled to stem from physics, particularly from mechanics or statistical physics, particle physics, or thermodynamics studied by Ludwig Boltzmann (1844–1906). Also in the field of biological evolution (macroevolution), equilibrium is debated as an important stage of development, e.g. within the theory of the punctuated equilibrium.

The first serious (although not rigorously justified) considerations about a general economic equilibrium were started by Antoine Augustin Cournot (1801–1877), who is also denoted as a predecessor of econometrics. Cournot described a model for monopoly and oligopoly and his equilibrium model for a duopoly is known as Cournot equilibrium. León Walras (1834–1910) is considered to be the father of the equilibrium economics. Cournot and Walras had consistent logical thoughts (Düppe & Weintraub, 2016) but did not prove the existence of equilibrium. Only Abraham Wald (1902–1950) presented a proof of existence of a competitive equilibrium for specific models of production and consumption in 1935–1936. Wald used a simple version of Kakutani's fixed-point theorem in his proof which was forgotten for a long time (Móczár, 2020). It remained however unclear whether Wald's results may be useful for economics (Düppe & Weintraub, 2016).

In game theory, John F. Nash (1928–2015) derived the optimal strategy for non-cooperative games. His main result known as Nash equilibrium was proposed in a very elegant and short paper in 1950 using Kakutani's fixed point theorem. He contributed to optimal strategies for more complicated games or mathematical models, which have found interesting economic applications e.g. for financial markets (Samuelson, 2016) or modeling trends in regional development (Silva et al., 2013). Nash won the Nobel prize in Economic Sciences in 1994 for the analysis of equilibria in the theory of non-cooperative games. Still, even the overview by Holt & Roth (2004) appraising Nash admits that the current economics may exploit Nash equilibrium especially for small situations, while large situations require the concept of competitive equilibrium. However, game theory remains purely mathematical and its applications to human behavior have been criticized as controversial, also because game theory was not primarily designed for the purpose to be used to model human behavior.

The main rigorous result in the theory of the general economic equilibrium was proven by Kenneth Arrow (1921–2017) and Gérard Debreu (1921–2004), who both won the Nobel Prize in Economic Sciences for their contributions to general economic equilibrium theory and its rigorous reformulation. Arrow obtained it in 1972 and Debreu in 1983. Particularly, they used a fixed point theorem of Brouwer to prove the existence of equilibrium for a solvable set of equations that correspond to production and consumption.

Supplements to the equilibrium theory have been derived also quite recently. Numerical methods for finding solutions of generalized Nash equilibrium problems were developed by von Heusinger et al. (2012). Equilibrium for an oligopolistic market with non-cooperative players (firms) was investigated by Outrata et al. (2016) and equilibrium between fast and slow trading (in a stock market) by Biais et al. (2015). If repeated identical markets are considered, a statistical equilibrium has been investigated. Other attempts for equilibrium, e.g. in the context of sustainable development (Cialowicz, 2017), do not however seem to reflect recent criticism of equilibrium approaches as such.

The general economic equilibrium, which is explained in every current macroeconomics textbook, requires an equilibrium-based way of economic thinking. We can say, although this is not usually admitted in the literature, that the relying on the concept of equilibrium implicitly assumes a linear, deterministic, rational, machine-like economy with a perfect elasticity. We perceive these properties as assumptions, which may be violated under fractal-structured economic conditions.

From the point of view of the economic doctrine, the neoclassical economic school is intensively concerned with equilibrium and conditions for its existence. Friedrich August von Hayek (1899–1992) appraised equilibrium, while Keynesians consider the very concept of equilibrium as useless, especially in an economic crisis. The general equilibrium theory was refused by critics of neoclassical economics (Düppe & Weintraub, 2016) claiming that current complex socio-economic issues need a paradigm shift to non-equilibrium economics. Nevertheless, equilibrium remains to be a fundamental concept in financial markets describing the equality of demand and supply of financial capital (Večeř, 2019).

3. FRACTAL SOCIETY, FRACTAL ECONOMY, AND CHAOS THEORY

Fractal (or multifractal) structures were theoretically investigated by Benoît Mandelbrot (1924–2010), the father of fractal geometry, or by the physicist Ilya Prigogine (1917–2003) in the context of nonlinear dynamic systems. In various fields of natural sciences, fractal structures have been observed; to be specific, fractals played the role in the Darwinian evolution or have been observed within the structure of the DNA. In general, fractal structures can be described as self-similar, self-developed and self-organized; in other words, one assumes that their high organization automatically appears from chaos. In economics, the properties of fractals and chaos are appealing e.g. for modeling of self-regulatory economic mechanisms (Redko & Sokhova, 2017).

Also in the current sociology or demography, fractals start to play their role as well, because the human society is highly organized while an individual typically lives in small neighborhood (social bubble) and the social distances among such groups (bands, cliques) are large even if their geographical distances are actually very small. Thus, fractal structures have obtained attention of economists, politicians or managers. It is in fact a consequence of the fractal structure of the society that psychological and social distances among people are increasing and people feel isolation, social alienation, apathy, or big distance from their community, although the information technology actually shortens the real (physical) distances among them or among devices.

The economy in a fractal society may possess a number of features immanent to fractal structures. Particularly, economic time series may have bizarre trajectories and the whole economy may be highly complex, irregular, unpredictable and highly vulnerable due to possibly severe consequences of small unimportant events.

Economic data may look like arising from a fractal process. Such idea is true not only for big or complex data, for which fractals definitely represent a suitable approach (Lahmiri & Bekiros, 2020), but actually also for common economic data, which are available in a classical setting with the number of observations n exceeding the number of variables p. Data analysis tools stemming from the idea of fractals rely on the assumption (or empirical experience) that real data sometimes (or perhaps often) possess some form of scaling. This means that it is realistic to assume that the distances between points are governed by a certain scaling law (Briggs, 2015).

Fractal-based modeling of economic data considers the data to represent a fractal structure, i.e. the data are assumed to bear a scaling property with a certain (but unknown) single value of the scaling exponent, which represents a parameter uniquely characterizing the scaling. However, if the scaling is not the same (homogeneous) across the whole data space, the concept of fractals is extended to multifractals. Data with a multifractal structure can be described as granularized or highly fragmented and their scaling exponent depends on the position of a particular point in the data space, as exploited by Biais et al. (2015) for recommending attractive investment decisions.

If economic data are analyzed and their fractal structure is taken into account, interesting results may be obtained particularly in the context of financial time series. A remarkable recent application of fractals was presented by Chen et al. (2017), who analyzed time series of freight rates (prices) of several bulk ships (the largest cargo ships). In the paper, an efficient pre-processing was applied to estimate the severity of the multifractal structure of the data. In R software, there is already a specialized package DChaos available for a multifractal time series analysis (Sandubete & Escot, 2021).

4. LIMITATIONS OF HUMAN DECISION MAKING

In contrary to automatic decision making performed by artificial intelligence, humans may exploit their tacit knowledge, which can be defined as a context-dependent practical knowledge (domain knowledge, expert knowledge) within the given context of the (e.g. economic or managerial) decision task. However, we have to admit on the other hand that human thinking is severely biased and often based on emotions. This irrationality was investigated and popularized by the psychologist Daniel Kahneman (2011), the Nobel Prize winner in Economic Sciences in 2002, and more recently by Tetlock & Gardner (2015).

The limited capacities of human decision making have become especially apparent in the chaotic era of the COVID-19 pandemic. Recently, one can namely encounter a flood of misinformation, fake news, prejudices, and cyber propaganda on social media. Every individual should combat misinformation in order to stay realistic, but many cannot distinguish what is the truth and what is not. We believe that this is again a consequence of the fractal structure of the society. In fact, human decision making can be explained by mental processes with a hierarhical structure. However, purely mathematical models without psychological dimensions cannot be successful in mimicing human decision making; the indescribable features of human thinking are especially manifested in the conditions of a fractal society.

5. DECISION SUPPORT AND RELATED METHODS OF STATISTICS OR INFORMATION THEORY

As human decision making is not sufficiently objective and trustworthy, decision support systems as very complex systems have been developed for a variety of economic or managerial decision tasks. Such systems allow to either assist humans in decision making, or to perform the decision making fully automatically. We consider them very perspective for the conditions of a fractal society and discuss their decision making aspects in this section. Decision

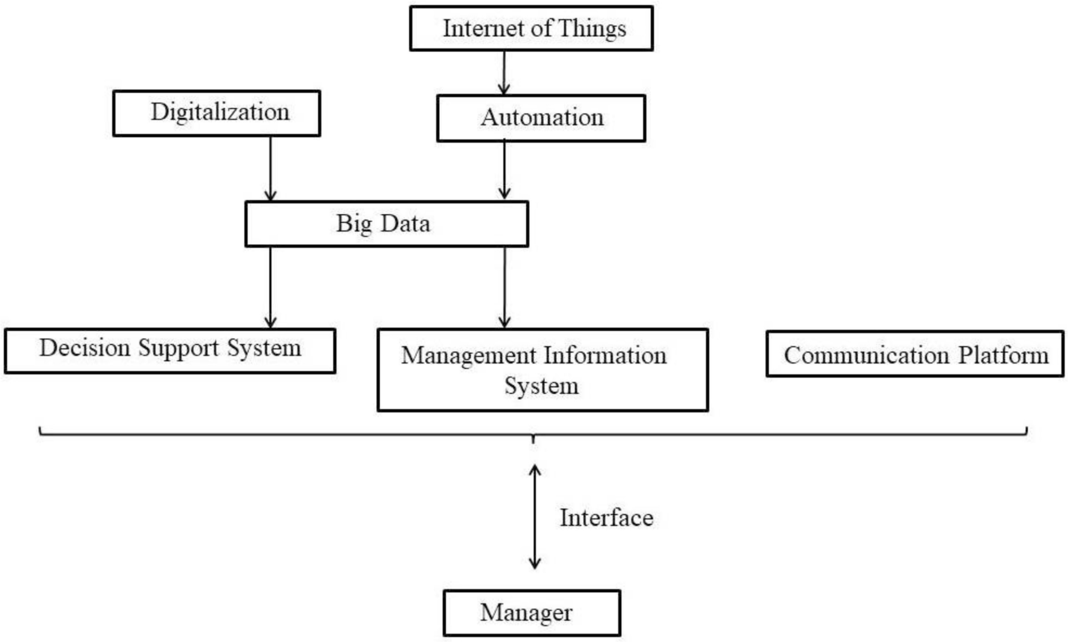

Figure 1. Scheme of managerial decision making exploiting advanced artificial intelligence tools. These are able to process massive data, which become increasingly available due to the recent technological progress

support systems have the ability to reflect typical current trends such as high complexity and/or contamination of the data. In fact, decision support systems can be also perceived as irreplaceable tools for the analysis (automatic analysis if possible) of big economic data.

Figure 1 shows how recent trends (including the progress of information technology) contribute to transforming everyday practices of management decision support. The so-called internet of things (i.e. connected networks of devices or softwares) accelerates automation processes in industrial production, which together with an omnipresent digitalization lead to a production of massive data. We stress here that a managerial decision support system should not be obtrusive for the user. Thus, we recommend the system to be connected with the management information system so that the manager does not have to copy the data from one software system to another manually. For the same reason, it is beneficial to have the system connected with a communication platform, which is nowadays so commonly used for online communication to overcome social distances.

The quality of the data used for decision making tasks remains to be crucial. While the volume of available data keeps increasing rapidly, the contamination of data e.g. by severe noise or gross measurement errors may increase as well. Decision making in economic or managerial tasks has the aim to come to a certain practical recommendation, while uncertainty must be understood as one of the aspects influencing the outcome (Kalina & Tichavský, 2020). Constructing a rule allowing to decide for one alternative among several possibilities is a task of classification analysis (Kalina & Duintjer Tebbens, 2015).

The methods suitable for the analysis of big data (with a large number of observations n) often require efficient algorithms for a fast computation. Some of statistical methods, which are theoretically suitable for big data, are implemented in commercial software in a way that is unsuitable for big data applications. Another important requirement expected from statistical methods for big data is their comprehensibility (i.e. possibility to present a clear interpretation) for the economic or managerial problem of interest.

Dimensionality reduction is commonly used as a preliminary or assistive prior to the statistical analysis of big data (Kalina, 2014). If the dimensionality reduction is not performed prior to a more sophisticated analysis of the big data, one must take resort to computationally demanding methods (Harrell, 2015). However, the performance of various methods for mining big economic data have not been systematically compared. Still, powerful and perspective tools for a reliable dimensionality reduction of big data are currently investigated (Kalina & Schlenker, 2015) together with properties of available methods of multivariate statistics and data mining for the big data context. Reducing the dimensionality can be perceived as one of possible approaches within the task of model selection (Večeř, 2019), i.e. for finding the appropriate model that as simple as possible but still able to explain the given data reliably.

Decision support tools should consider also the information flow. To give an example, dominant financial markets are known to have influence on less important ones, or a time series of stock prices may have influence on the time series of cryptocurrency returns. In both situations we speak about information flow, i.e. transfer of information (about the performance of the stock market) with causal effects on financial returns in another market. Information flow has been subject of theoretical studies in the context of information theory and/or cybernetics. Available attempts to evaluate (quantify) the effect of one stock market on another by means of measures of information theory focused on the use of transfer entropy as a measure allowing to evaluate the transfer of information.

6. EXAMPLE: CREDIT RISK MANAGEMENT

This section is devoted to a particular example of decision making in the field of credit risk. In the recent monograph by Witzany (2017) on credit risk management, credit scoring was characterized as an important methodology for modeling and predicting the credit of individual bank customers. A careful detection of individuals or companies not able to repay a mortgage will be even more important in the unstable post-COVID-19 economies (Wakode, 2020) with a fractal structure. The banks must evaluate all individual clients (loan applicants) in order to decide to which of the two groups they belong:

[I] Clients able to repay (redeem) the loan in time,

[II] Clients likely to fail to repay the loan.

The models for the decision making are learned over a database of available data from the past, while the model must be only (e.g. once per two years) re-validated and/or updated.

Specific decision support systems have been implemeneted and successfully applied also to tasks of credit risk management as overviewed e.g. by Ignatius et al. (2018).

Particularly, the system of Luo (2020) aims at assessing creditworthiness of private companies before they lend money (if their request for a loan is approved). The system used the logistic regression, which is currently the most common method in credit risk. The classification methods however suffer here from the fact that the two groups of clients are imbalanced (unequal). Therefore, we decided for including an oversampling technique allowing to improve the classification performance in our computations. Such tool is based on random generation of new observations as combinations of the available ones. Although Big Data have been many times applied in corporate credit scoring and prediction (Witzany, 2017), we are not aware of a publicly available credit risk dataset with a large number of variables. Therefore, we present now original results of recently proposed methods for a well known but rather small dataset.

The Australian credit risk dataset is publicly available in the UCI repository (Dua & Graff, 2017). It was preliminary analyzed in Kalina (2017), however with a focus on the effect of dimensionality reduction and without a cross validation. Here, we work with n=690 observations and p=14 variables, where there are 6 continuous and 8 categorical variables. There are 383 clients (observations) in class I and the remaining 307 clients belong to class II. We use several standard as well as recently proposed classifiers including robust neural networks (Kalina, 2013). The results are evaluated in a 5-fold cross validation. We use R software for the computations.

We use several well known classifiers. Methods proposed only recently contain interquantile robust versions of multilayer perceptrons and radial basis function (RBF) networks and their robust versions based on the loss function of the least weighted squares (LWS) estimator (see Kalina (2015)); these were proposed and investigated by Kalina & Vidnerová (2020). Fixed parameters $\tau = 0.15$ and $\tau = 0.85$ were used for the interquantile approaches, while linear weights were used for the LWS-based approaches. A support vector machine classifier is used with a Gaussian kernel. All versions of multilayer perceptrons use 2 hidden layers with 16 and 8 neurons, respectively, and all versions of RBF networks use 70 radial units. Optimal values of regularization parameters (i.e. for regularized versions of logistic regression and for support vector machines) were determined in a 5-fold cross validation.

Table 1 evaluates the results in the form of the classification accuracy, which is formally defined as the ratio of the number of correctly classified cases to the total number of observations. This is presented either in an autovalidation (autoverification) study, where the classification accuracy is evaluated over the entire (training) dataset, or in a 5-fold cross validation performed in a standard way. Autovalidation is however known to usually lead to (possibly severely) biased results, while cross validation represents an attempt for an independent validation.

To interpret the results in Table 1, there is a remarkable difference between the results of the (biased) autovalidation and the cross validation. In fact, methods performing the best in the autovalidation are not necessarily the best in the cross validation. The classification tree, so popular in management applications, turns out to be outperformed by all other methods presented here; the tree was used with such settings of parameters, which are default in R software.

Table 1. Results of the credit risk management example of Section 6. Classification accuracies are presented here, which are evaluated for an autovalidation study and also for a 5-fold cross validation study

Method	Autovalidation	5-fold cross validation
Logistic regression (LR)	0.88	0.72
L_1-regularized LR	0.90	0.74
L_2-regularized LR	0.90	0.75
Linear discriminant analysis	0.86	0.71
Support vector machines	0.90	0.73
Classification tree	0.83	0.67
Multilayer perceptron (MLP)	0.85	0.70
Interquantile MLP	0.85	0.73
LWS-based MLP	0.84	0.72
RBF network	0.87	0.73
Interquantile RBF network	0.86	0.76
LWS-based RBF network	0.85	0.75

The best classification results are obtained with LWS-based RBF network, i.e. a version of RBF networks with a robust loss function proposed only very recently. This method is based on assigning weights to individual observations so that the most reliable (least outlying) obtain the largest weights.

Indeed, neural networks are without any surprise more flexible tools compared to others (e.g. compared to logistic regression, as it represents only their special case). Regularization brings benefits in this dataset and it is worth mentioning that it improves the result of logistic regression compared to its plain (i.e. the most popular) version.

To conclude the example, reliable decision making requires to use very recent data analysis tools. We can see here the benefit of robust analysis of data compared to standard (non-robust) procedures, which remain vulnerable to the presence of outliers in the data. We believe that the importance of these robust tools will be increasing together with an increasing contamination and uncertainty in the data (Kalina et al., 2019) under the conditions of the fractal economy.

7. CONCLUSIONS

As the current society is affected by recent global trends, decision making in economic and managerial tasks have to reflect the transforms of the economical environment in every individual country of the world. This paper is focused on consequences of the rise of fractal-structured economies on decision making tasks. Still, a number of issues has not been explicitly mentioned in this paper. One important issue is a need for new analytical tools for an efficient and robust analysis of big economic data. Another necessity is a reform of the education of future managers, who should be able to keep up with the technological progress and with the transform of management practices after the COVID-19 pandemic. In the literature, increasing attention has been also paid to evidence-based approaches such as evidence-based decision making (Brownstein et al., 2019); inspired by medicine and healthcare (Kalina & Zvárová, 2013), it has already found successful results e.g. in financial applications within the so-called evidence-based investing or factor investing (Dimson et al., 2017). We also plan to investigate model selection (automatic method selection, meta-learning) methods for financial and economic data.

Acknowledgement

The work was supported by the project GA21-19311S ("Information Flow and Equilibrium in Financial Markets") of the Czech Science Foundation.

References

Arrow, K.J. & Debreu, G. (1954). Existence of an equilibrium for a competitive economy. Econometrica, 22, 265–290.

Biais, B., Foucault, T., & Moinas, S. (2015). Equilibrium fast trading. Journal of Financial Economics, 116, 292–313.

Briggs, J. (2015). Fractals: The Patterns of Chaos. Discovering a New Aesthetic of Art, Science, and Nature. Brattleboro: Echo Point Book & Media.

Brownstein, N.C., Louis, T.A., O'Hagan, A., & Pendergast, J. (2019). The role of expert judgment in statistical inference and evidence-based decision-making. American Statistician, 73, 56–68.

Chen, F., Tian, K., Ding, X., Li, T., Miao, Y., & Lu, C. (2017). Multifractal characteristics in maritime economics volatility. International Journal of Transport Economics, 44, 365–380.

Cialowicz, B. (2017). Demand sphere as a co-engine of sustainable development. European Journal of Sustainable Development, 6 (4), 465–474.

Dimson, E., Marsh, P., & Staunton, M. (2017). Factor-based investing: The long-term evidence. Journal of Portfolio Management, 43 (5), 15–37.

Dua, D., & Graff, C. (2017). UCI machine learning repository, available at [http:// archive.ics.uci. edu/ml].

Düppe, T., & Weintraub, E.R. (2016). Losing equilibrium: On the existence of Abraham Wald's fixed-point proof of 1935. History of Political Economy, 48, 635–655.

Faggini, M., Bruno, B., & Parziale, A. (2019). Does chaos matter in financial time series analysis? International Journal of Economics and Financial Issues, 9 (4), 18–24.

Harrell, F.E. (2015). Regression Modeling Strategies with Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis. 2nd end. Cham: Springer.

von Heusinger, A., Kanzow, C., & Fukushima, M. (2012). Newton's method for computing a normalized equilibrium in the generalized Nash game through fixed point formulation. Mathematical Programming, 132, 99–123.

Holt, C.A., & Roth, A.E. (2004). The Nash equilibrium: A perspective. Proceedings of the National Academy of Sciences, 101, 3999–4002.

Ignatius, J., Hatami-Marbini, A., Rahman, A., Dhamotharan, L., & Khoshnevis, P. (2018). A fuzzy decision support system for credit scoring. Neural Computing and Applications, 29, 921–937.

Kahneman, D. (2011). Thinking, Fast and Slow. New York: Farrar, Straus and Giroux.

Kalina, J. (2013). Highly robust methods in data mining. Serbian Journal of Management, 8 (1), 9–24.

Kalina, J. (2014). On robust information extraction from high-dimensional data.

ДОНОШЕЊЕ ОДЛУКА КОЈЕ ОДРАЖАВАЈУ ФРАКТАЛИЗАЦИЈУ ДРУШТВА

Jan Kalina

Извод

Иако се главна економска доктрина ослања на концепт равнотеже, садашње друштво се у последње време суочава са озбиљним изазовима. Иако можемо доживети постепени успон идеала друштва знања, сматрамо да ће друштво (и економије широм света) имати фракталну структуру према моделима које истражује теорија хаоса. Овај рад је фокусиран на доношење одлука посебно у економским, или менаџерским задацима и њиховим трансформацијама услед промене парадигме ка фракталном друштву у неравнотежним економским условима. Разматрани су статистички и информационо-теоријски аспекти подршке одлучивању и анализиран је и приказан пример доношења одлука из области управљања кредитним ризиком.

Кључне речи: подршка одлучивању, економска равнотежа, менаџмент, кредитни ризик, теорија информација, теорија хаоса

Serbian Journal of Management, 9 (1), 131–144.

Kalina, J. (2015). Three contributions to robust regression diagnostics. Journal of Applied Mathematics, Statistics and Informatics, 11 (2), 69–78.

Kalina, J. (2017). High-dimensional data in economics and their (robust) analysis. Serbian Journal of Management, 12 (1), 157–169.

Kalina, J., & Duintjer Tebbens, J. (2015). Algorithms for regularized linear discriminant analysis. In Proceedings of the 6th International Conference on Bioinformatic Models, Methods and Algorithms (Bioinformatics '15), Lisbon: Scitepress, pp. 128–133.

Kalina, J., & Schlenker, A. (2015). A robust supervised variable selection for noisy high-dimensional data. BioMed Research International, 2015, 320385.

Kalina, J., & Tichavský, J. (2020). On robust estimation of error variance in (highly) robust regression. Measurement Science Review, 20, 6–14.

Kalina, J., Vašaničová, P., & Litavcová, E. (2019). Regression quantiles under heteroscedasticity and multicollinearity: Analysis of travel and tourism competitiveness. Ekonomický časopis/Journal of Economics, 67, 69-85.

Kalina, J., & Vidnerová, P. (2020). Regression neural networks with a highly robust loss function. In Analytical Methods in Statistics, Maciak, M. et al., Eds. Springer Proceedings in Mathematics & Statistics, 329, 17–29.

Kalina, J., & Zvárová, J. (2013). Decision support systems in the process of improving patient safety. In E-health Technologies and Improving Patient Safety: Exploring Organizational Factors, A. Moumtzoglou and A. Kastania, Eds. Hershey: IGI Global, 71–83.

Klioutchnikov, I., Sigova, M., & Beizerov, N. (2017). Chaos theory in finance. Procedia Computer Science, 119, 368–375.

Lahmiri, S., & Bekiros, S. (2020). Big data analytics using multi-fractal wavelet leaders in high-frequency Bitcoin markets. Chaos, Solitons & Fractals, 131, 109472.

Liu, Z., Ye, Y., Ma, F., & Liu, J. (2017). Can economic policy uncertainty help to forecast the volatility: A multifractal perspective. Physica A, 482, 181–188.

Luo, C. (2020). A comprehensive decision support approach for credit scoring. Industrial Management & Data Systems, 120, 280-290.

Móczár, J. (2020). The Arrrow-Debreu model of general equilibrium and Kornai's critique in the light of neoclassical economics. Journal of Banking, Finance and Sustainable Development, 1, in press.

Moreno-Jiménez, J.M., & Vargas, L.G. (2018). Cognitive multiple criteria decision making and the legacy of the analytic hierarchy process. Estudios de Economía Aplicada, 36, 67–80.

Outrata, J.V., Ferris, M.C., Červinka, M., & Outrata, M. (2016). On Cournot-Nash-Walras equilibria and their computation. Set-valued and Variational Analysis, 24, 387–402.

Redko, V.G., & Sokhova, Z.B. (2017). Processes of self-organization in the community of investors and producers. Studies in Computational Intelligence, 736, 163–169.

Samuelson, L. (2016). Game theory in economics and beyond. Journal of Economic Perspectives, 30 (4), 107–130.

Sandubete, J.E., & Escot, L. (2021). DChaos: Chaotic time series analysis. R package version 0.1-6 [https://CRAN.R-project.org/package=DChaos].

Silva, S.T., Mota, I., & Grilo, F. (2013). The use of game theory in regional economics: A quantitative retrospective. Papers in Regional Science, 94, 421–441.

Tetlock, P.E., & Gardner, D. (2015). Superforecasting: The Art and Science of Prediction. New York: Crown Publishers.

Večeř, J. (2019). Dynamic scoring: Probabilistic model selection based on utility maximization. Entropy, 21 (1), 36.

Wakode, S. (2020). Efficacious scrutinizing of COVID-19 impact on banking using credit risk metrics. International Journal of Finance & Economics, 6 (3), 51–56.

Witzany, J. (2017). Credit risk management. Pricing, Measurement, and Modeling. Cham: Springer.