Development of information system to model cyclic fluctuations of economic time series

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Abstract. Decision making in the economy demands tools to find the most effective, cost-affordable, and optimal solutions. Besides, there is a high necessity to have possible solutions not for tactic needs but for strategic as well. Business and economic analysts of all levels of economic management are eager to put up the user-friendly software, apps, or solutions to support their analytic and forecasting attempts. In the epoch of the claimed Industry 4.0, rapid digitization and on-line of recent quarantine events, the information systems, and any computer support is the best possibility and treasure. This paper is devoted to the idea of possible computer support for the analysis and forecasting of economic dynamics. Particular attention is paid to the time series modelling and detecting of its cyclic component. The majority of economic time series have the seasonality or other cycling inside of its dynamics, that could dramatically pervert the linear trend forecast or any other determinate direction of the trend. The proposed information system is quite user-friendly but the low error way provides a potential user with the tool of cyclic component forecasting. The methodology is grounded in the Assimakopouloscyclicity filter. The case of Denmark's GDP quarterly since 1995is presented to test and confirm the system's effectiveness in acquiring knowledge about the dynamics of the economic system. The sufficient accuracy of the implemented forecasting methods is presented.

Keywords: Information system, Economic cycle, Assimakopoulos approach.

1 Introduction

A large proportion of open databases for the analysis are represented in the time series view. There is often a need to analyze the main components of the time series: the trend, seasonal, cyclic, and random components. The presence of each component is explained by different reasons. The trend component that determines the direction of process change is most often analysed in the time series. Its presence is usually explained by demographic or technological factors. There are numerous opportunities for trend modelling, in particular, the regression approach that allows different shapes of a trend component modelling: linear, quadratic, exponential, and so on. It is also possible to detect the magnitude of the trend by using certain smoothing methods: the sliding average method, exponential smoothing [14], double Brown exponential smoothing, triple Brown exponential smoothing, Holt-Winters' model [7].

It is no less common to exploit cycles and seasonal variations that show periodic changes over a certain period. For example, in agriculture and demography the modelling of monthly or quarterly fluctuations during the year, daily fluctuations during the week, and so on are in the scope. Some methods have been developed to highlight seasonal variations, including the Holt-Winters' seasonal models and the seasonality index model. Econometrists often model seasonal fluctuations by adding some dummy variables to the regressions. It allows determining the effect of each season on the variable under study.

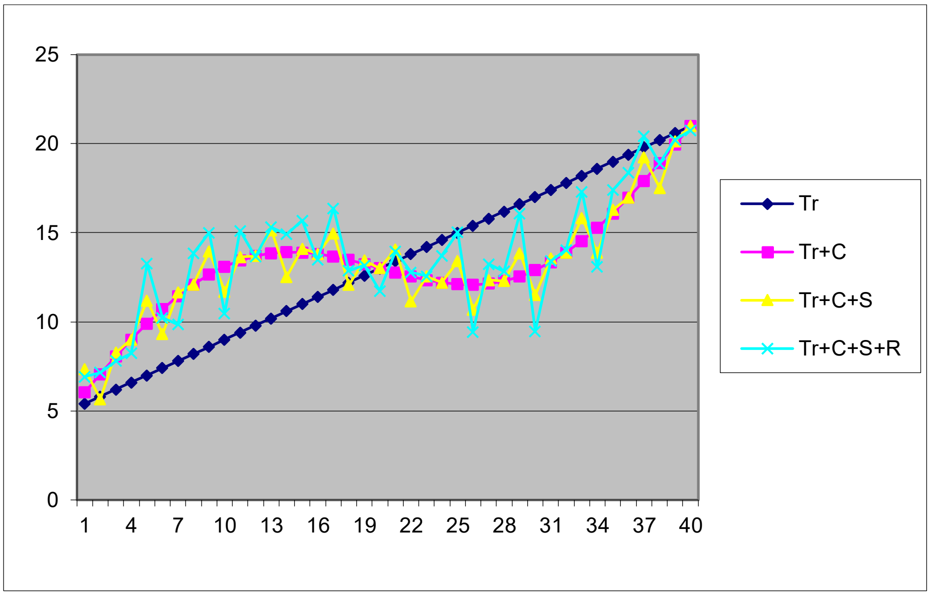


Fig.1. Time series components. Source: authors' compilation.

As a rule, all parts of the time series that are not included in the trend or seasonal component are referred to as the random component. There are some possibilities for creating models for random component analysis, in particular ARMA models [6]. However, researchers do not always carefully examine how this random component is formed. For example, if a variable under study is affected by weather, which is currently very difficult or impossible to predict over a long period, then it is referred to as a random component. It also might include the effects of the cyclic component. This is uncertainty happens because, in practice, analysts rarely work with enough long time series reasoning by the significant changes in the methodology for collection and processing economic data. However, if such a series still exists, then it is necessary to detect a cyclic component (Fig. 1).

In practice, the cycle extraction from the trend causes considerable difficulties caused by the interconnections. The trend shows a long-term change direction. Whilst the cyclical component is a rhythmic fluctuation of indicators by a certain value, which can be observed only for a rather long period. One of the approaches to isolate cyclic sequence fluctuations is the Assimakopouloscyclicity filter [1]. It is not mathematically complicated, so it can be easily programmed and is most practical to use, although relatively little known.

The purpose of this paper is to propose an information system that based on an imported database could eliminate the cyclical fluctuations in time series and simultaneously detect both the magnitude of such fluctuations and other components of the series.

Structurally, the article consists of the following sections. The literature review presents an analysis of publications with methods for identifying the cyclic component in different fields, identifying their advantages and disadvantages. The methodology section describes the formal rules for allocating cyclic components in time series. The following section demonstrates the ability of an information system to split the time series into components. Finally, the last section provides conclusions.

2 Related works

The literature review on the cyclic component detection in the time series is quite vast. However, the main idea of this paper is to match the research gap in the studies of time series in the economic and social fields, along with the literature on the IT systems in the economy, particularly to put in the forecasting tools topic.

A significant problem in the economic situation forecasting and analyzing is to correctly identify the beginning of each phase of the cycles. This issue is still causing considerable debates among scientists because even under the modern development of statistical science, different researchers differently determine the presence of a new phase of the cycle. At present, there is no clear interpretation of the change in cycle phases, and therefore the cycle length. The latter magnitude is generally associated with the prime problems in the cycle formalization. Since even in retrospect there is no clear interpretation of the start and endpoint of the cycle: they are hardly determined.

Of course, the current state of issues provokes the necessity to develop a model for determining the length of cycles and the time of their phase change. There were attempts to develop such a mechanism using Markov chains [31]. Nevertheless, such a mechanism, on the one hand, is rather bulky and difficult to use, and on the other hand, has no restrictions on cycle phase changes, which makes it impossible to appeal to the classical definition of the cycle.

In economics, the economic cycle refers to fluctuations with a fixed period. The most important types of cycles [27] are:

- Kitchin warehouse cycle, 3-4 years long;

• Juglar fixed-investment cycle of 7-11 years;
• Kuznets infrastructural investment cycle (15-25 years);
• Kondratiev wave of 45-60 years;
• Forrester cycle of 200 years.

The logic behind the proposed cycle lengths is determined only by the authors' understanding of the time it takes to change a particular product, production facility, or economic model. Still, it should be noted that all of these developments were based on data from the late XVII - early XX centuries. Though, the speed of economic change and new technologies launch has completely changed the idea of how the phases of the cycle change, what its real length is. Indeed, in the XVIII-XIXth centuries governments did not inspect the effects of cyclical fluctuations, and consequently did not respond to them. Then it says about the relative purity of scientific analysis of the crisis length. Yet, as early as the XXth century, following the Great Depression, governments began to use different mechanisms to avoid or eliminate the crisis. Such attention to crisis analyses could not affect the real economy and the behaviour of people who changed their expectations about the frequency of crisis and their devastating consequences. Although it did not lead to the complete abolition of the economic crisis, it has significantly changed the incidence and new expectations of people. In particular, if people previously feared crisis due to temporary loss of life and a rise in the cost of living, then today, the population expects only extremely dire crisis on a global scale with the devastating force like the 2020 pandemic coronavirus has shown.

Also, it should be understood that globalization is a process of synchronization in crisis phenomena. The paper [17] analyzes the level of economic growth synchronization in 185 countries. It was shown that a high level of synchronization was observed from 1990 to 2011. During this period global shocks accounted for about 77% of GDP dispersion in developed European countries. At the same time, regional shocks have played a greater role in the CIS, Asia, Africa and the Middle East. The results indicated a higher level of synchronization in industrialized countries. Also, it should be noted that according to [17] the global financial crisis led to an increase in a global synchronization of economic growth, but the level of synchronization decreased at the beginning of recovery.

Accordingly, a particular problem of long-term forecasting is the allocation of cycles of different lengths. If all the cycles were of a predetermined length, if their objective manifestation was not impeded by numerous factors, then the possibility of mathematical determination of groups of cycles could be clear and simple. In fact, to determine the cycles of different lengths the researcher needs a sufficient number of observations. For example, to determine a cycle of 45-60 years (Kondratiev long waves), a series of at least 200-300 observations should be analyzed. Since the cycles are allocated with annual data, it is necessary to have the dynamics of some economic process at comparable prices for 300 years. That is a statistical challenge of any country in the world.

Thus, at the present stage of statistics, it is impossible to determine cycles with a large wavelength by mathematical methods alone. Having only more or less reliable and comparable observations over the last 100-120 years, one can speak of the allocation of small and medium cycles. However, it should be noted that the required statistics only exist in some countries. The geopolitical redistribution of the 1990s, the creation of new states, make it impossible to comprehensively analyze and test any method on real data.

This problem is not limited to economics. For instance, cyclical fluctuations are present in the climate change on the planet. Nevertheless, due to the destructive activities of mankind, increasing the carbonation of the economy, the impact of cycles has significantly decreased compared to the global temperature increase trend, which does not allow it to be distinguished by standard econometric methods. Global warming and climate change have recently led to environmental, physical and medical consequences, including extreme weather events. Compared to 1850, the average temperature in the Northern Hemisphere has become higher by about 1.4 degrees Celsius, and in the Southern Hemisphere by 0.8 degrees Celsius [23]. Despite numerous agreements to limit atmospheric emissions, for the first time in four years, CO_2 emissions increased in 2017 leading to atmospheric concentrations of up to 403 ppm compared to the pre-industrial level of 280 ppm. Over the past half-century, emissions have grown exponentially and temperatures have risen linearly [28].

Afterwards, there is a assembly of studies dedicated to the cyclic fluctuations modelling in the ecosystems to forecast chaos state (i.e. [3, 13]). Mathematical models have shown that species interactions can produce chaos. However, the field evidence of chaos in natural ecosystems is still quite singular. In [3] it had shown that natural ecosystems can sustain continued changes in species abundances and that seasonal forcing may move forward these non-equilibrium dynamics to the edge of chaos. The next set of published studies is considering the fluctuations and cycling in time series analyses implementing it to the ecology [4-5], macroeconomics and investing [12, 25, 29], demographics and social economics [20, 22, 24]. Most of the studies are devoted to modelling short-term fluctuations in the presence of seasonal and long-term patterns, dealing with time-varying confounding factors and modelling delayed ('lagged') associations between exposure and outcome [4].

The major part of researches determines the cyclic component as regular or periodic fluctuations around the trend, excluding the irregular component, revealing a succession of phases of expansion and contraction [16]. The cyclical component can be viewed as those fluctuations in a time series, which are longer than a given threshold, e.g. 1½ years, but shorter than those attributed to the trend [26]. The best example is a business cycle, which typically lasts several years, but where the length of the current cycle is unknown beforehand, like the famous Canadian lynx data – the number of lynx trapped each year in the McKenzie river district of northwest Canada (1821-1934). These clearly show a periodic population cycles of approximately 10 years. The cycles are not of fixed length – some last 8 or 9 years and others last longer than 10 years [30].

At the same time, the realisation of time-series analyses for the economic modelling is not exhausted just with tools of R, Eviews, Excel and other known software. More and more companies are trying to support their analysts with quick, simple and effective software that able to be helpful even for the person without deep econometrics education, like logistics, marketing or production managers etc. Within the artificial society, launching Industry 4.0 and the new era of robotization, there is a higher demand on the computational intelligence that would be able to produce friendly interface software with the application of the complicated but quite effective fozzy-logic-based computing, econometrics modelling, particularly time series modelling, neurocomputing[19]. The business struggles to solve complex computational problems in the economic systems by using conventional mathematical methods but in a friendly way for a broad group of managers and decision-makers [2, 9, 21].

Highlight, that detecting of cycling is highly important for the economy. The nature of the cyclicality of economic variables or political decisions is inherently linked to the concept of the business cycle [11]. The simplistic idea of cyclicality research is to isolate cycles from the overall economic dynamics and analyze their dynamic relationship within the processes under study. Thus, the problem of correct allocation of the cyclical component of economic development is central to such studies. Besides, this problem has been and remains one of the most important in economic theory, as evidenced by the broad list of Nobel laureates who have made significant contributions to the development of the problem (Finn Kidland and Edward Prescott, Robert Engle and Clive Granger, Christopher Sims and Thomas Sargent) [8].

From the point of economic policy decisions, pro-cyclical discretionary economic decisions stimulate the phases of the economic cycle - in case of uplift they stimulate economic activity, in case of recession they cool the economy [18]. A pro-cyclical economic policy increases the amplitude of business cycle fluctuations. Acyclic economic policy does not affect cycle parameters. Counter-cyclical policy cools the economy in the face of overheating trends and stimulates the recession phase. Determination of cyclicality characteristics in terms of business cycle theory and economic politics is not always the same. If government spending increases in the business cycle growth phase and falls in the fall phase (positive correlation), then we have an example of pro-cyclical policy on both approaches. If, for example, to take into consideration the central bank's discount rate, then raising it during an economic upturn and lowering it during a recession (positive correlation) we will formally consider pro-cyclical behaviour, but in terms of monetary policy, we are dealing with counter-cyclical measures [10].

To highlight the cycles of an economic process, the first question that needs to be answered is the trend characteristics of the dynamic process. Choosing a rational forecasting strategy is one of the fundamental problems in any sector of the economy. The arsenal of economic cybernetics methods contains a large number of various methods of economic dynamics (time series) analysis which distinguishing feature is considerable computational complexity and, as a consequence, the impossibility of practical application without the use of modern software. The purpose of economic dynamics analysis is the conceptualization of a comprehensive computer system to support the forecasting ability. Mostly the researchers and economists are eager to obtain qualitative conclusions about the nature of the system behaviour to predict it and then use the results in the management of the economic system. Thus, the conceptual components of the complex economic system analysis and forecasting are monitoring, forecasting and subsequent management. This reflects the main stages of economic and mathematical modelling (research, forecasting and management of the economic system) and provides an integrated approach to the study of the economic system dynamics and the use of its results [15]. Hence, the example of one of the solutions to the indicated problem is presented in this paper.

3 Methodology

As already mentioned, the allocation of cyclicity of time series fluctuations is an important practical task. First, it is necessary for macroeconomic research, because it is based on the analysis of the current economic cycle phase. Moreover, it enables to formulate an appropriate anti-cyclical or pro-cyclical government policy. Secondly, it is no less important to identify cyclical fluctuations for microeconomic modelling, in particular for the company sales analysis. At the same time, analysts often face a certain problem, which is the lack of long time series. This is due to the life cycle of the company, a particular product, accounting software, and so on. In any case, only a few firms can boast of having such long time series on which it would be realistic to distinguish cyclical fluctuations. Therefore, the model that allows this to be done with the least amount of observations, especially in automatic mode, should be valued by analysts quite highly.

In the literature review, it was pointed out that in fact there are not many effective models used to detect cyclic oscillations, and therefore the choice is narrowed to those that are able to work with short time series. We have chosen the Assimakopoulos filter, which independently determines the length of the cycle on the basis of calculations, and makes it possible to determine the cyclic component of the time series, using only the initial data series.

To present the information system we consider the Assimakopoulos method for allocation of cycles in the economic time series. The idea behind the cyclic isolation method is to eliminate cyclic effects based on the so-called θ-transformation. Such a filter can eliminate cyclic fluctuations of any length. Let the momentary trend in time t be equal

$$tr_t = y_{t+1} - y_t, \ t = \overline{1, T-1}.$$

The new sequence is built by the rule:

$$\tilde{y}_t = \begin{cases} \dfrac{y_{t+1} + y_{t-1}}{2}, if \left|tr_t - tr_{t-1}\right| > 0 \text{ and } \left|tr_t - tr_{t-1}\right| = \max\limits_{k=2,T} \left\{\left|tr_k - tr_{k-1}\right|\right\}, \\ y_t, \text{in other cases.} \end{cases}$$

It should be noted that this method does not apply to the linear trend series. We assume that the time series is believed to have a "pyramidal" structure. It is based on a straight line that refers to the simplest long-term trend. This line is superimposed on cyclical effects, starting with the longest end and ending with the shortest. In other words, the cyclic effects are superimposed on the trend line in a strictly decreasing order, depending on their length. This reasoning is consistent with the assumption that small cycles exist as part of long waves. Finally, the pyramid ends with the imposition of a random component.

The use of θ-transformation first eliminates the time series of the random component, then the shortest cycle, and ends with the trend selection. To use θ-transformation to eliminate cyclic effects, we enter θ-index:

$$\theta_p = \frac{100}{\max\limits_{t=1,T} y_t - \max\limits_{t=1,T} y_t} \max_{t=2,T-1} \{|tr_t - tr_{t-1}|\}$$

Let's consider step by step the structure of the method iterations:

Step 1. Calculate the two additional observations to be added at the beginning and at the end of the time series.

Step 2: Initially estimate the length of the longest cycle that appears in the time series.

Step 3. Implement θ-transformation for a new time series derived from the original row by adding new elements in step 2.

Step 4. Calculate θ-index for each newly received time series.

Step 5. End the process when the time series θ_p - index refers to the largest cycle estimate (as initially estimated in step 2). Thus, the time series obtained contain the trend of the initial time series.

Then a regression on the first and last n observations is constructed to obtain additional observations. Most commonly researchers use $n = 5$.

It should be noted that the above method eliminates the time series of all cyclic fluctuations whose length is less than selected in step 2. It cannot be guaranteed that the maximum possible cycle length will be selected.

It has been practically found that there is a relationship between the θ_p - index and the length of the longest cycle, which can be determined from the time-series graph. It has been shown that the l_k length of cycles using θ-transformation disappear if $\theta_p \le k$. The relationship between θ_p and k for monthly data is the following:

- θ_p = 1, the length of the eliminating cycle is equal to 5 (period of 5 months);
- θ_p = 0.1, the length of the eliminating cycle is equal to 12 (seasonal cycles);
- θ_p = 0.02, the length of the eliminating cycle is equal to 45-60 (period of 4-5 years);
- θ_p = 0.007, the length of the eliminating cycle is equal to 80-125 (period of 7-10 years).

The above method can be widely used in forecasting a variety of economic information. It should be noted that generalization of known techniques can (as in the case of exponential smoothing) improve the accuracy of forecasts.

Thus, when running the program for the initial sequence (which is the database), the maximum and minimum values are calculated. Further, based on a simple linear regression (usually taking the step n = 5), the additional values are calculated having 0 and k + 1 positions, where k is the number of database elements. Based on the difference between the k-th and (k-1)-th element of the sequence, the trend is calculated. Based on the difference between the i-th and (i-1)-th value of the trend, the difference in the trends is counted. One can select the largest value of the trend difference by the module. Next, it is appropriate to use the formula that calculates theta-index:

$$\Theta_p = \frac{1}{\max L - \min L} \cdot \max_{i=2}^{N-1} 100 \cdot \{|Tr_i - Tr_{i-1}|\}$$
$$= \frac{1}{\max L - \min L} \cdot \max_{i=2}^{N-1} 100 \cdot \{|X_i - 2X_{i-1} + X_{i-2}|\}$$

where N –is the number of observations in the original time series, max L - min L – the difference between the maximum and the minimum value of the observations of the original series.

If the theta index is greater than 0.007, we can speak about the strong role of the random component in the sequence. Then a new smoothed sequence is calculated, each kth term of which is the arithmetic mean between the (k –1) and (k + 1) level of the previous sequence. This sequence will already be somewhat smoothed relative to the previous one. As far, it allows you to determine the value of the theta index for already calculated sequence. Since we are interested in the maximum deprivation of a given sequence of the cyclic component, the calculation was carried out until the difference between the theta indexes of the obtained and the previous sequence would be less than 0.01.

4 Results: programme description

The program was developed by means of VBA for Microsoft Excel. When opening an application file, the user enters the standard Microsoft Excel file, where the original database has already been imported. However, users can download their data to run. When you make changes to the database, the user sees an application menu that appears automatically. There the analyst can either go directly to the analysis and get acquainted with the information about the program and its authors.

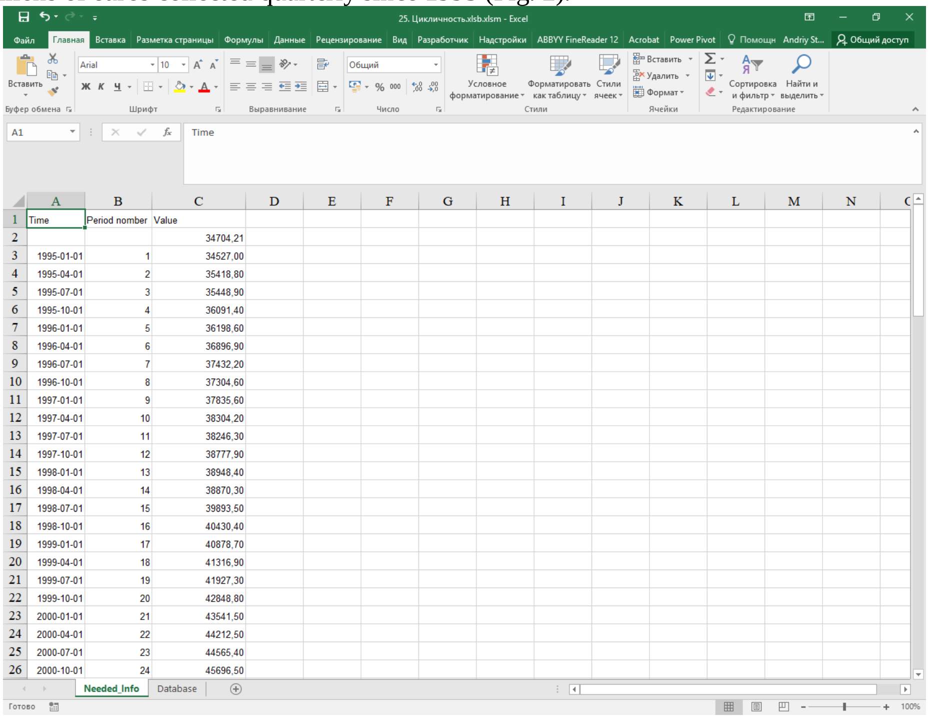
The application interface has been specifically designed to be concise so that the user can intuitively work with the program without confusion in different windows, tabs, and the like. The user can at any time start analyzing the time series, which is to derive the most smoothed sequence, which is a trend estimate, the value of the cyclic component, and a graph that reflects cyclic fluctuations relative to the trend. The program works for any size of the database, which is a significant advantage of it, and the process of work itself is fast, start-up-intuitive.

The system is not overloaded with the choice of different parameters, because the user only loads the required database, all parameters are calculated using the method Assimokoupolos within the code, so the user is completely burdened with the need for mathematical calculations. If the user is not familiar with the concept of theta index, it will be enough to see a graph that shows the cyclical fluctuations of the initial sequence relative to the trend, or he can read the instructions to the program.

Thus, one of the biggest advantages of this information system is its extraordinary ease of use. The user can make changes to the database if necessary to analyze another time series. The pressing "Go to Analysis" button is affordable even for a person who is unfamiliar with time series analysis, that makes the proposed IT decision users-friendly one.

5 Case example

As the case example, we propose a time series of the value of Denmark's GDP in millions of euros collected quarterly since 1995 (Fig. 2).



Time	Period nomber	Value
		34704,21
1995-01-01	1	34527,00
1995-04-01	2	35418,80
1995-07-01	3	35448,90
1995-10-01	4	36091,40
1996-01-01	5	36198,60
1996-04-01	6	36896,90
1996-07-01	7	37432,20
1996-10-01	8	37304,60
1997-01-01	9	37835,60
1997-04-01	10	38304,20
1997-07-01	11	38246,30
1997-10-01	12	38777,90
1998-01-01	13	38948,40
1998-04-01	14	38870,30
1998-07-01	15	39893,50
1998-10-01	16	40430,40
1999-01-01	17	40878,70
1999-04-01	18	41316,90
1999-07-01	19	41927,30
1999-10-01	20	42848,80
2000-01-01	21	43541,50
2000-04-01	22	44212,50
2000-07-01	23	44565,40
2000-10-01	24	45696,50

Fig.2. Data source. Source: Eurostat.

Running the program allows a user to make the necessary calculations (Fig. 3). The columns of the MS Excel sheet contain the name of each period, its ordinal number, the actual value of the time series, as well as two calculation columns: trend estimation and cyclic component estimation. Accordingly, if we subtract the value of the cyclic component from the real value, we can analyze the new time series without the influence of cyclicity. It is also possible to analyze separately the value of the column of the cyclic component, which allows us to find an economic justification for certain changes in the time series behavior.

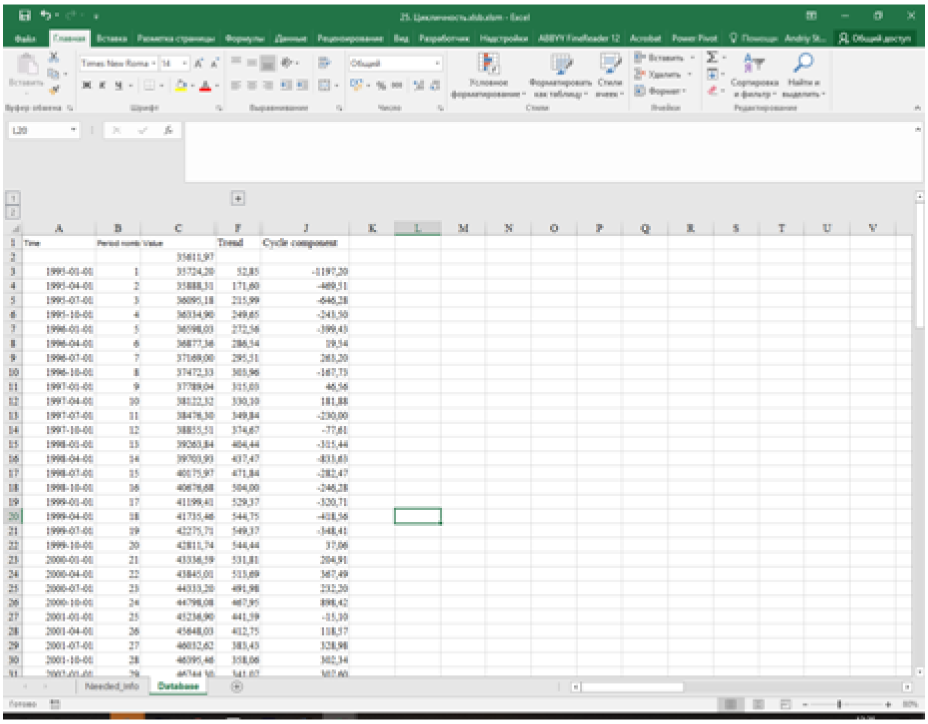


Fig.3. Information system calculations for obtaining the cyclic component of time series. Source: authors'.

Finally, one can construct a graph comparing the real value of the studied variable and the obtained forecast of the selected trend component (Fig. 4).

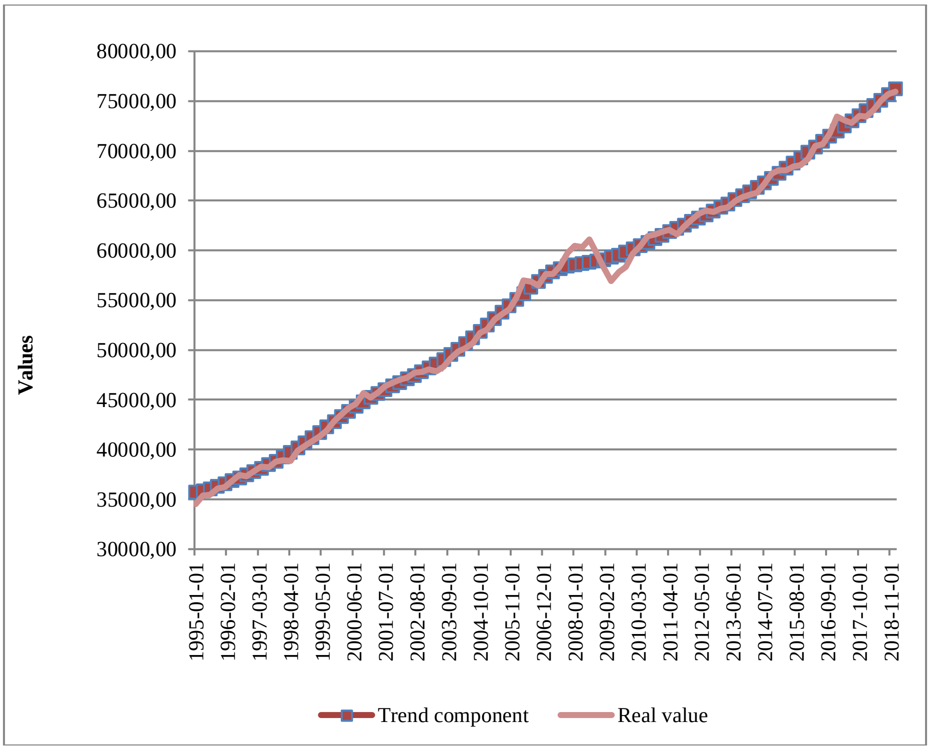


Fig.4.Trend component vs real data. Source: the calculations of the information system.

In the last step, one can build the dynamics of the cyclic component of the time series (Fig. 5). This graph is based on the calculated column of the cyclic component in Fig. 3.

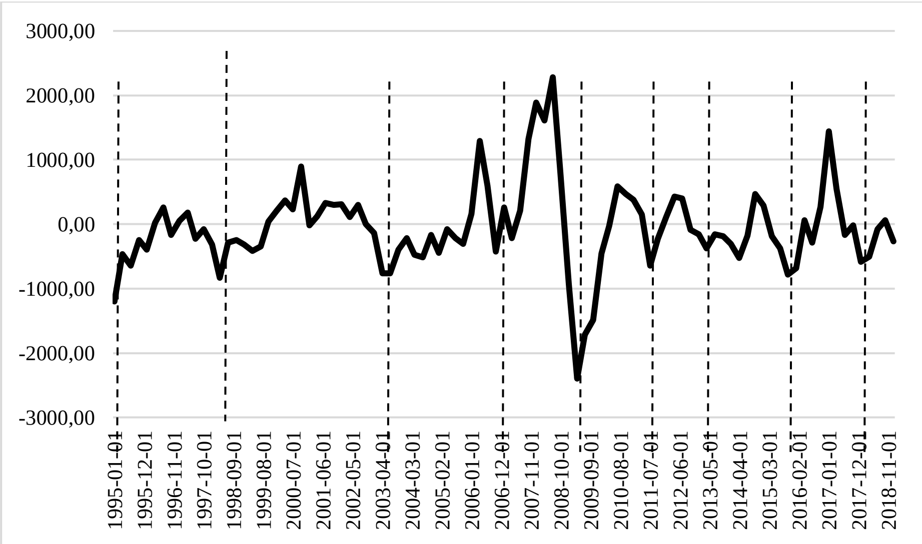


Fig.5**.** Cyclic component dynamics. Source: the calculations of the information system.

The graph allows determining the phase of economic growth from the beginning of observations until August 2008, when the global financial crisis began. But this growth was not homogeneous from 1996 to 2008. There were three small cycles: from January 1996 to April 1998, from May 1998 to April 2003, from May 2003 to December 2006. Finally, since 2007, the fourth cycle has come and ended with the financial crisis, that is, the end of a stronger long cycle. At the same time, the cyclical situation since 2009 has not been so clearly observed, because the governments of European countries, particularly Denmark, have pursued a stimulating fiscal and monetary policy, which has approved to be acyclic. But even under these conditions, the presented information system can identify three small uniform cycles of about 2 years in length, as well as the fourth wave with significant growth. If there had been no active state acyclic policy, a serious crisis would have been expected at the end of 2017 related to the end of the longer cycle. However, appropriate stimulus measures delayed the crisis. As it turned out for another short two-year cycle: the economic recession has been starting in the first quarter of 2020. Fig. 5 demonstrates the corresponding limits for the phases of the cycles, which can be determined from the data of the developed information system. It should be noted that this provides only a basis for the researcher for further analysis, as it is necessary to compare the obtained phase breakdown with the real economic or other factors that influenced the time series data. However, such an analysis must be individual in each case. For this paper example, it can be concluded that the lessons and consequences learned from the 2008 global financial crisis changed the size of short cycles (from about 3 to 2 years) but did not change the length of the longer cycle. Therefore, there were not 4 but 5 shorter cycles between crises.

As one can conclude, a series of cyclical fluctuations obtained employing the information system allows making as quite valuable conclusions, but also to predict the onset of economic, financial and other shocks. The better identification of cycles allows better policy reactions and enhances the attempts to predict naturally occurring cycles that is especially problematic if they are no longer naturally occurring.

6 Conclusions

The issue of allocation of the cyclic component is an important element of successful forecasting in all areas of activity. Correct allocation of the cyclic component in time series may be of interest to:

• governments and central banks to adopt changes to fiscal and monetary policies to avoid market distortions as a result of overproduction in certain sectors;

• managers at firms to formulate more adequate sales and procurement plans for the warehouse, create timely advertising campaigns to increase profits;

• ecologists to analyze climate change on the planet;

• doctors to analyze the recurrence of epidemic diseases;

• scientists to study a new class of time series voiding the cyclic component.

Obviously, further research should address how exactly economic and other cycles converge across countries, regions, industries. It will be able to provide information to shape relevant economic, environmental, health and social policies in the world.

The authors have created an information system that displays the smoothed sequence with the entered time series, which is a long-term trend, as well as the values of cyclic fluctuations with the further graphical display of the result. The program works simply and effectively, with repeated testing no problems were detected. This information system enables users to easily select cyclic fluctuations from an arbitrary time series. Obtaining this data allows researchers more often referring to the analysis of the cyclic component, motivating the study of dynamics and determining the factors that influence it.

With the help of the developed IT system, an example of a complex pre-forecast analysis of output time series in the field of economy is shown. The results of the application revealed the performance of the IT system and provided new knowledge about the objects of analysis and forecasting.

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References

1. Assimakopoulos, V.: A successivefilteringtechniqueforidentifyinglong-termtrends. Journal of Forecasting, vol. 14, 35-43 (1995)https://doi.org/10.1002/for.3980140104.
2. Barua, A., Kriebel, C., Mukhopadhyay, T.: Information technologies and business value: An analytic and empirical investigation. Information systems research, 6(1), 3-23.(1995).

3. Benincà, E., Ballantine, B., Ellner, S., Huisman, J.: Species fluctuations sustained by a cyclic succession at the edge of chaos. Proceedings of the National Academy of Sciences, 112(20), 6389–6394 (2015). https://doi.org/10.1073/pnas.1421968112
4. Bhaskaran, K., Gasparrini, A., Hajat, S., Smeeth, L., Armstrong, B.: Time series regression studies in environmental epidemiology. International Journal of Epidemiology. (2013). https://doi.org/10.1093/ije/dyt092
5. Blarer, A., Doebeli, M.: Resonance effects and outbreaks in ecological time series. Ecology Letters. (1999). https://doi.org/10.1046/j.1461-0248.1999.00067.x
6. Brockwell, P., Davis, R.: Time Series: Theory and Methods. 2d ed. Springer, New York (2009).
7. Chernyak, O., Stavytskyy, A.: Dynamic econometrics. KVIC, Kyiv (2000).
8. Clancy, D., Merola, R.: Countercyclical capital rules for small open economies. Journal of Macroeconomics, 54, 332-351 (2017).
9. Du, X., Deng, L., Qian, K.: Current Market Top Business Scopes Trend – A Concurrent Text and Time Series Active Learning Study of NASDAQ and NYSE Stocks from 2012 to 2017. Applied Sciences, 8(5).2076-3417 (2018).
10. Hailu, D., Weeks, J.: Can Low-Income Countries Adopt Counter-Cyclical Policies? International Policy Centre for Inclusive Growth, 92. (2016).
11. Jackson, L., Owyang, M., Soques, D.: Nonlinearities, smoothing and countercyclical monetary policy. Journal of Economic Dynamics and Control, 95, 136-154 (2018).
12. Kendall, B.: Chaos and Cycles. In: Encyclopedia of Global Environmental Change, Vol. 2: The Earth System: biological and ecological dimensions of global environmental change. (2002).
13. Kendall, M., Hill, A.: The Analysis of Economic Time-Series-Part I: Prices. Journal of the Royal Statistical Society. Series A (General). (1953). https://doi.org/10.2307/2980947
14. Kharlamova, G., Stavytskyy, A. Economic Modelling of Energy Security: Simulation of Economic Processes (Case of Ukraine Gas System). In: Proceedings of the 14th International Conference on ICT in Education, Research and Industrial Applications. Integration, Harmonization and Knowledge Transfer.ICTERI Workshops, vol. 2. pp. 128-143 (2018).http://ceur-ws.org/Vol-2104/paper_178.pdf
15. Korotayev, A: Toward Forecasting Global Economic Dynamics of the Forthcoming Years. Economic Policy, 1, 8-39(2017).
16. Lenzen, M., Pinto de Moura, M., Geschke, A., Kanemoto, K., Moran, D.: A cycling method for constructing input-output table time series from incomplete data. Economic Systems Research, 24(4), 413-432(2012).
17. Matheson, T.: The Global Financial Crisis: An Anatomy of Global Growth. International Monetary Fund Working Papers. (2013). https://www.imf.org/~/media/Websites/IMF/imported-full-text-pdf/external/pubs/ft/wp/2013/_wp1376.ashx
18. Mohanty, A., Mishra, B.: Is fiscal policy pro-cyclical or counter-cyclical? Evidence from India. Arthshastra Indian Journal of Economics & Research, 6(2), 7-19 (2017).
19. Palit, A., Popovic, D.: Computational intelligence in time series forecasting: theory and engineering applications. Springer Science & Business Media. (2006).
20. Partonen, T., Haukka, J., Viilo, K., Hakko, H., Pirkola, S., Isometsä, E., …Räsänen, P.: Cyclic time patterns of death from suicide in northern Finland. Journal of Affective Disorders. (2004). https://doi.org/10.1016/S0165-0327(02)00236-7
21. Perfilieva, I., Yarushkina, N., Afanasieva, T., Romanov, A.: Web-based system for enterprise performance analysis on the basis of time series data mining. In: Proceedings of the

First International Scientific Conference "Intelligent Information Technologies for Industry"(IITI'16), pp. 75-86 Springer, Cham. (2016).
22. Richards, T.: Weather, nutrition, and the economy: Short-run fluctuations in births, deaths, and marriages, France 1740-1909. Demography. (1983). https://doi.org/10.2307/2061235
23. Ritchie, H., Roser, M.: CO_2 and other Greenhouse Gas Emissions. (2018). https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions
24. Row, J., Wilson, P., Murray, D.: Anatomy of a population cycle: The role of density dependence and demographic variability on numerical instability and periodicity. Journal of Animal Ecology. (2014). https://doi.org/10.1111/1365-2656.12179
25. Şen, Z.: Innovative trend significance test and applications. Theoretical and Applied Climatology. (2017). https://doi.org/10.1007/s00704-015-1681-x
26. Shumway, R., Stoffer, D. Time series analysis and its applications: with R examples. Springer. (2017).
27. Stavytskyy, A.: Modelling of Cycles in World Economy. Finances of Ukraine, 9. 96-102 (2008).
28. Stavytskyy, A.: Influence of modern geopolitical challenges on state's economic security. Bulletin of Taras Shevchenko National University of Kyiv. Economics, 4(199). 45-55 (2018). doi: https://doi.org/10.17721/1728-2667.2018/199-4/6
29. Tapia Granados, J.: Macroeconomic fluctuations and mortality in Postwar Japan. Demography. (2008). https://doi.org/10.1353/dem.0.0008
30. Wang, E., Cook, D., Hyndman, R.: A new tidy data structure to support exploration and modelling of temporal data. Journal of Computational and Graphical Statistics, 1-13(2019).
31. Zatonatska, T., Stavytskyy, A.: Modelling of Cycling Economic Growth in Ukraine.Economic Cybernetics, 3-4 (45-46). 11-22. (2007).