
Application of Technical Analysis Stochastic Oscillator for Early Detection of Epidemiological Changes Based on Covid-19 Data in Poland

Submitted 10/09/24, 1st revision 25/09/24, 2nd revision 01/10/24, accepted 15/10/24

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Abstract:

Purpose: The aim of the research was to test the possibility of using a type of technical analysis indicator – the stochastic oscillator – to predict the progression of an epidemic based on the Polish COVID-19 epidemic data.

Design/Methodology/Approach: Data on active COVID-19 cases in Poland in 2020/22 were used as a research material. The stochastic oscillator was used to determine turning points in the prediction of epidemiological changes.

Findings: It was demonstrated that the best performance is achieved with the slow, smoothed version of the oscillator and the following parameters: %K14 and %D7. Despite a few erroneously generated changes in the incidence trend, most signals were verified correctly.

Practical Implications: The stochastic oscillator, most commonly used in finance to predict market trends, may also find application in research related to predicting disease progression.

Originality/Value: Studies such as those in this article, based on epidemiological data, have not been conducted before.

Keywords: Simulation Methods, Simulation Modeling, Public Health.

JEL codes: C53, C63, I18.

Paper type: Research article.

Conflict of interest: The author declares that has no conflict of interest in relation to the publication of this manuscript.

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1. Introduction

In late 2019, a new infectious disease emerged in Wuhan, China, causing serious respiratory problems and often leading to fatal pneumonia. The World Health Organization (WHO) declared the pandemic on 30 January 2020 to prepare for the fight against this highly infectious virus causing COVID-19. The WHO has confirmed that the cause of the outbreak was a coronavirus (type 2) causing severe acute respiratory distress syndrome: SARS-CoV-2 (Cucinotta and Vanelli, 2020; Trill, 2020; World Health Organization, 2024; Lai, Shih, Ko, Tang, and Hsueh, 2020).

The pandemic spread to 114 countries in such a short time that it was dubbed as the greatest threat in the history of infectious diseases (Adak, Majumder, and Bairagi, 2021; Walls, Park, Tortorici, Wall, McGuire, and Veesler, 2020). As of 28 April 2024, over 775 million confirmed cases and more than seven million deaths have been reported globally. As of 28 April 2024, over 775 million confirmed cases and more than seven million deaths have been reported globally (World Health Organization, 2024).

Effective, proven tools for monitoring and prediction of the progression of pandemic diseases could make it possible to reduce the number of cases and deaths. For this reason, the development of increasingly effective methods of epidemiological data analysis is an important task. This could allow more accurate prediction of dynamic changes in the spread of diseases.

Mathematical models have been used in epidemiology for years. State health organizations have used them to monitor the situation and take appropriate steps to mitigate infectious diseases, e.g.: HIV (Djordjevic, Silva, and Torres, 2018), Zika virus (Ndaïrou, Area, Nieto, Silva, and Torres, 2018) or Ebola virus (Rachah, and Torre, 2016).

There are a number of models currently used in epidemiology, ranging from the conventional SIR model to more complex solutions (Brauer, Castillo-Chavez, and Feng, 2019). The name of the SIR model is an acronym of possible health conditions: S – susceptible/healthy, I – infected and R – recovered/immunized. The basic SIR models have been modified to include more possible health conditional, including transitional ones. The result are more complex models, such as the SIRS (Levin, Hallam, and Gross, 2012), SEIR (Murray, 2002) and others (Hethcote, 2000), are also in use.

Many scientists have worked on mathematical models capable of predicting disease progression at a country level. The purpose of the resulting epidemiological dynamics model was to provide the information required by the state authorities to introduce appropriate strategies to prevent and control epidemics. Creating a model

that would provide reliable estimates in a timely manner was of paramount importance.

The stochastic oscillator, like other technical analysis indicators, is most often used in financial analysis to detect trends, cycles and turning points. Alongside fundamental analysis and market analysis, technical analysis is a core tool used by investors. It makes it possible to predict market developments and, in particular, to detect early signals of imminent ups and downs (Wu and Diao, 2015).

The aim of the research undertaken was to verify another possible application of one of technical analysis indicators – the stochastic oscillator. The stochastic oscillator is a smoothed and normalized indicator of momentum, i.e. the rate at which a process accelerates or decelerates. The use of the stochastic oscillator in medical science allows the analysis of any time series to detect turning points. With these features, it can also be a promising solution for epidemiological research.

2. Material and Methods

The aim of this research was to test the possibility of using the stochastic oscillator, a type of technical analysis indicator, in predicting the progression of an epidemic based on the Polish COVID-19 epidemic data.

Data of active COVID-19 cases in Poland from 01/04/2020 to 10/03/2022 were used for the analyses. The data was taken from Michał Rogalski's civic project "COVID-19 w Polsce" (COVID-19 in Poland". The sources of information used to create the database were reports published by the Ministry of Health, WSSE (Provincial Sanitary and Epidemiological Station), PSSE (District Sanitary and Epidemiological Station), provincial offices and data collected for public information requests (Rogalski, 2024).

The difference between the number of cases and the number of recoveries on a given day was taken as the number of active COVID-19 cases.

One of technical analysis indicators, the stochastic oscillator, was used to determine turning points in predicting epidemiological changes. The stochastic oscillator, like other technical analysis tools, focuses exclusively on historical data. It is based on momentum, i.e., the rate at which a given variable accelerates or decelerates.

The stochastic oscillator is a smoothed and normalized indicator of momentum which can take values from 0 to 100. It consists of two lines. The first line %K is a measure of the relative position of a given variable. The second line %D is the signal line – the moving average of %K. The point of intersection of %K with %D is a signal indicating the possibility of a decrease or increase in, for example, the number of disease cases (i.e. a change in trend).

The %K line is calculated using the following formula:

$$\%K = \left(\frac{x_n - x_{\min}}{x_{\max} - x_{\min}} \right) * 100\%$$

where:

x_n – value of the variable on the n th day of observation,

$x_{\min}$ – the lowest value of the variable over the last k observations,

$x_{\max}$ – the highest value of the variable over the last k observations.

When analysing stock market data, the value of k is usually 5, which is the number of observations in one week. In contrast, the %D line is determined as a three-day moving average ($n=3$) of %K. The levels of overbought and oversold for this indicator are set at 80 and 20 respectively (Wu and Diao, 2015).

To reduce the number of erroneous signals generated by the %K and %D lines, smoothing should be applied. This involves taking the old %D line as the new %K line, while the new %D line is the moving average of the new %K line. In epidemiological studies, it seems more reasonable to use this smoothed variant, hereafter referred to as the slow version of the oscillator, as proven long-term predictions are expected. The slow version of the oscillator reduces the number of erroneous signals, but it also has a disadvantage: it slows down the oscillator's response (Wu and Diao, 2015).

The stochastic oscillator indicates signals of a change in a trend. Three situations signal an increase in active COVID-19 cases:

- the point at which the %K indicator crosses the line from below at the level of 20;
- the point at which the %K line crosses the %D line within the 0-20 area from below;
- the point at which there is divergence of the %D line with the given variable in the 0-20 area.

In turn, the following situations signal a decrease in active COVID-19 cases:

- the point at which the indicator crosses from above the line at the level of 80;
- the point at which the %D line crosses the %K line from above within the 80-100 area;
- the point at which there is divergence of the %D line with the given variable in the 80-100 area.

In economic sciences, where the stochastic oscillator is used in stock market forecasting, the generally accepted variant $k=5$ and $n=3$ is used. In this study based on epidemiological data, $k=7$, which is the number of observations per week was used. In addition, simulations were carried out to select moving average parameters (n) for the signal lines in order to ensure the optimal performance of the indicator for long-term forecasts. What was taken into account was the relevance of the indicator used at 7 days, 14 days, 21 days and 28 days after signal generation. Different combinations of variants were tested for $\%K_n$ and $\%D_n$, for $n \in \{1,7,14,21,28\}$.

3. Results

In the first stage of the analysis, parameter selection was simulated for $\%K$ and $\%D$ signal lines. The aim was to select periods which, using a stochastic oscillator, would give the highest level of valid signals of a change in trend in the number of COVID-19 patients. When using the unsmoothed $\%K$ line (marked as $\%K_1$) and changing the parameters for the $\%D$ moving average line, the highest percentage of correctly generated signals was obtained with $\%D_{21}$, i.e., when the $\%D$ signal line was the moving average of the $\%K$ line over 21 days.

This means that the three-week period was, in this case, the most effective period in predicting a decrease or increase in disease incidence. However, its correctness was only 45.7%. This means that more than half of the signals generated were incorrect. It was therefore decided to smooth the $\%K$ line to reduce the amount of captured noise. A new slow (smoothed) oscillator with better performance was created as a result to generate more correct signals in the long term (Table 1).

The best result among all the cases considered was obtained for the slow oscillator: $\%K_{14}$ and $\%D_7$. This means that the $\%K$ line was the 14-day moving average of the unsmoothed $\%K$, line, while the $\%D$ line was the 7-day moving average of the $\%K_{14}$ line. In this way, as many as 27 signals were obtained during the study period, of which an average of 71.3% were generated correctly. Therefore, it should be concluded that a two-week period for the $\%K$ line and a one-week period for the $\%D$ line should be used to achieve the best forecasting results (Table 1).

The same result (71.3% correct signals) was obtained for $\%K_{28}$ and $\%D_7$. A similar performance (71.0% correct signals) was also achieved for $\%K_{21}$ and $\%D_7$. However, in these cases, the number of total signals generated was found to be much lower than for $\%K_{14}$ and $\%D_7$ (20 and 25 for $\%K_{28} + \%D_7$ and $\%K_{21} + \%D_7$ respectively) (Table 1).

In the 7-day forecast, the highest percentage of correct signals (75.0%) was obtained for $\%K_{28}$ and $\%D_7$. In the 14-day forecast, the highest percentage of correct signals (72.0%) was obtained for $\%K_{21}$ and $\%D_7$. In the 21-day forecast, the highest percentage of correct signals (74.1%) was obtained for $\%K_{14}$ and $\%D_7$. In the 28-day forecast, the highest percentage of correct signals (74.1%) was obtained for $\%K_{14}$

and $\%D_7$. It is therefore reasonable to assume that the $\%D_7$ signal line gave the best results in each of the cases analysed (Table 1).

For the most effective 7-day forecast, $\%K_{28}$ should be used, while for the 14-day forecast $\%K_{21}$ is the optimal choice. In the case of long-term forecasts (21 days and 28 days), $\%K_{14}$ had the highest accuracy. It is also worth noting that as the smoothing period of $\%K$ increased, the number of signals generated decreased from an average of 72 for $\%K_1$, to an average of 20 signals for $\%K_{28}$ (Table 1).

Table 1. Parameter selection for the stochastic oscillator based on the number of active COVID-19 cases in Poland from 01/04/2020 to 10/03/2022.

n $\%K_n$	for n $\%D_n$	Number of signals	Percentage of correctly generated signals in the forecast:				
			7 days	14 days	21 days	28 days	Average
1	7	76	36.8%	39.5%	44.7%	46.1%	41.8%
1	14	77	40.3%	42.9%	48.1%	48.1%	44.9%
1	21	70	41.4%	44.3%	48.6%	48.6%	45.7%
1	28	66	37.9%	42.4%	47.0%	47.0%	43.6%
7	7	31	58.1%	51.6%	58.1%	58.1%	56.5%
7	14	38	52.6%	50.0%	55.3%	52.6%	52.6%
7	21	34	50.0%	55.9%	55.9%	52.9%	53.7%
7	28	30	60.0%	56.7%	56.7%	53.3%	56.7%
14	7	27	66.7%	70.4%	74.1%	74.1%	71.3%
14	14	30	56.7%	63.3%	63.3%	60.0%	60.8%
14	21	26	65.4%	65.4%	65.4%	61.5%	64.4%
14	28	24	70.8%	66.7%	66.7%	62.5%	66.7%
21	7	25	72.0%	72.0%	72.0%	68.0%	71.0%
21	14	28	64.3%	60.7%	60.7%	60.7%	61.6%
21	21	23	73.9%	65.2%	65.2%	60.9%	66.3%
21	28	22	72.7%	68.2%	68.2%	63.6%	68.2%
28	7	20	75.0%	70.0%	70.0%	70.0%	71.3%
28	14	22	63.6%	54.5%	54.5%	54.5%	56.8%
28	21	20	65.0%	60.0%	55.0%	60.0%	60.0%
28	28	17	70.6%	64.7%	58.8%	64.7%	64.7%

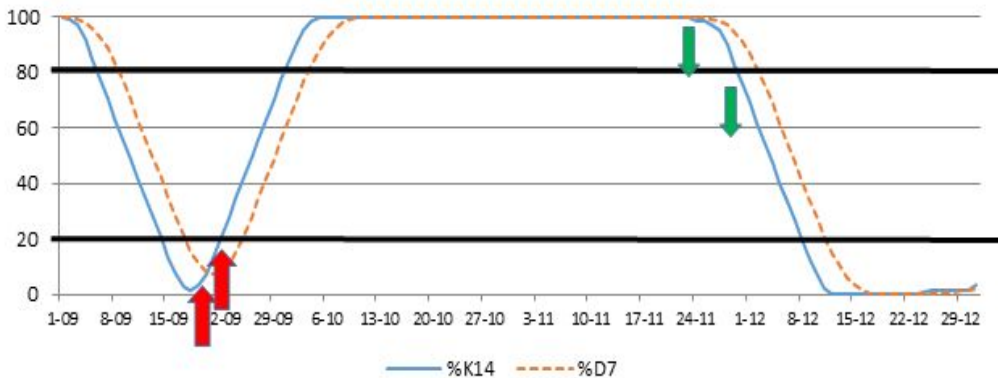
Source: Own elaboration.

The subsequent part of the analysis focused on the signals generated by the slow stochastic oscillator for the most effective variant, i.e. $\%K_{14}$ and $\%D_7$.

The first surge of COVID-19 cases in Poland occurred between 1 September and 31 December 2020. During this period, the stochastic oscillator indicated two consecutive signals of an increase in the number of active cases on 21 and 22

September and two signals of a decrease in this parameter: on 21 and 30 November (Figure 1).

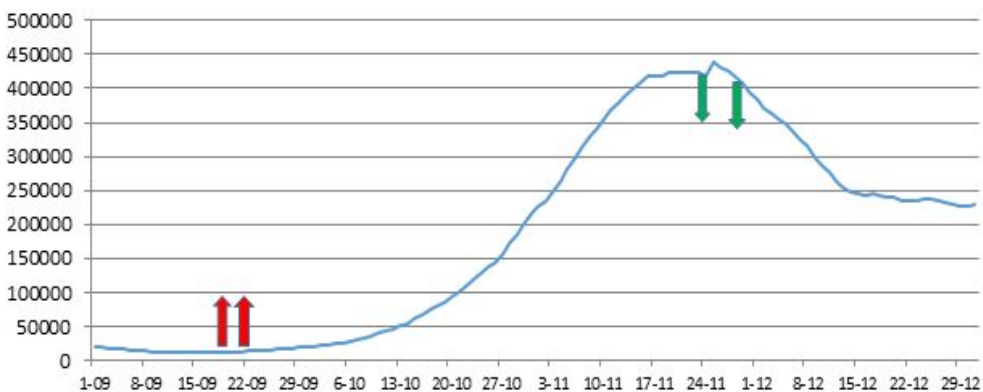
Figure 1. Slow stochastic oscillator, number of active COVID-19 cases in Poland from 1 September to 31 December 2020.



Source: Own elaboration.

All oscillator signals during this period can be considered correct. Increase signals were followed first by a slow and then by a sharp increase in disease incidence. On the other hand, after decrease signals – the number of active cases began to drop (Figure 2).

Figure 2. Number of active COVID-19 cases in Poland from 1 September to 31 December 2020.

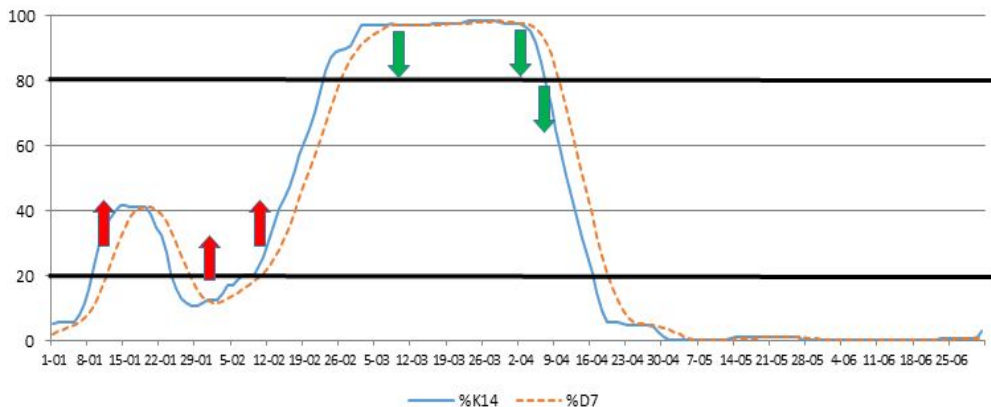


Source: Own elaboration.

Below are the signals generated by the slow stochastic oscillator, for the number of active COVID-19 cases in Poland in the first half of 2021. During the study period, three consecutive signals of increase in the number of active cases per day were

generated for: 9 January, 31 January and 7 February, while three consecutive signals of decrease were generated for: 9 March, 29 March and 7 April (Figure 3).

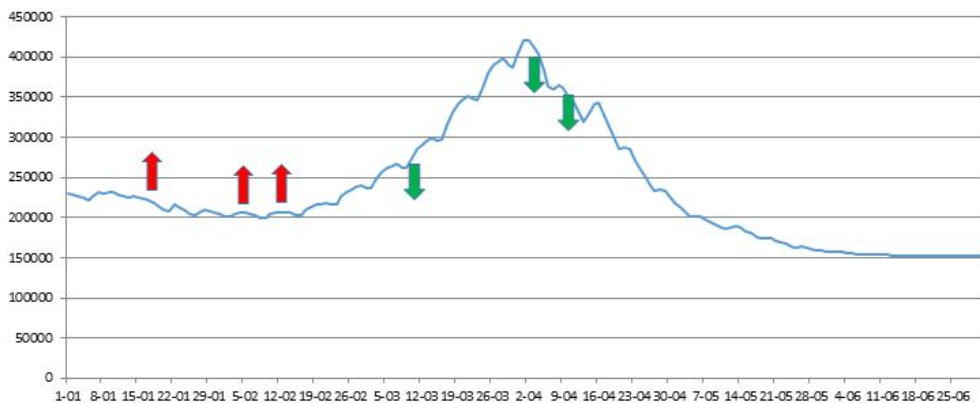
Figure 3. Slow stochastic oscillator, numbers of active COVID-19 cases in Poland in the first half of 2021.



Source: Own elaboration.

Also during this period, the signals generated were correct. The decrease signal for 9 March is questionable. Perhaps it was generated erroneously, as the number of cases kept increasing for three weeks thereafter. On the other hand, it is possible to interpret this signal as an early prediction of the decline, which occurred exactly 25 days later (Figure 4).

Figure 4. Numbers of active COVID-19 cases in Poland in the first half of 2021.

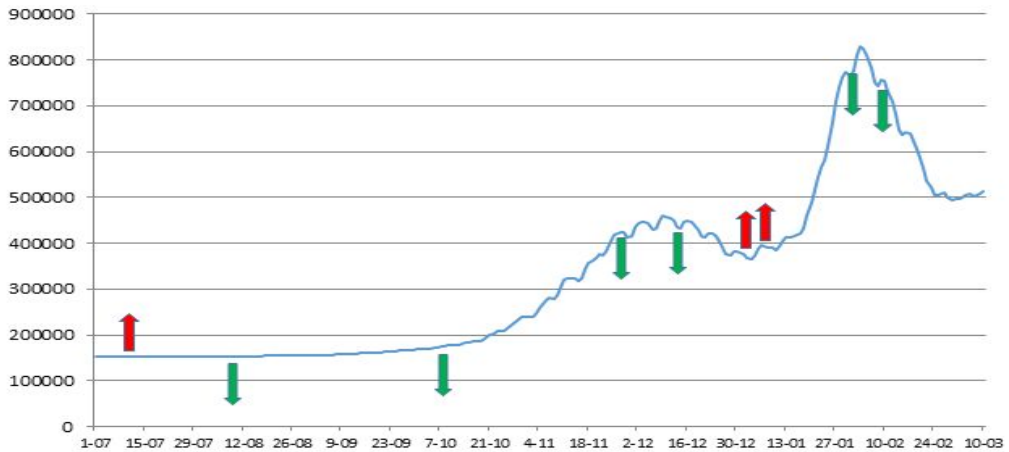


Source: Own elaboration.

Between 1 July 2021 and 10 March 2022, the oscillator indicated three increase signals (11 July, 5 January and 8 January) and six decrease signals (8 August, 10 October, 28 November, 15 December, 31 January, 11 February). As can be seen in the figure below, most of the signals were generated correctly. Only the signals of 8

August and 10 October should be regarded as erroneously generated because these signals were followed by an increase in disease incidence, rather than decrease (Figure 5).

Figure 5. Numbers of active COVID-19 cases in Poland between 1 July 2021 and 10 March 2022.



Source: Own elaboration.

Despite a few erroneously generated signals presented in the figures, most of the signals were verified correctly, which indicates the effectiveness of the technical analysis method using the stochastic oscillator. This corroborates the possibility of an innovative application of a tool originally developed for financial analysis. The stochastic oscillator has proven to have great potential in identifying increase and decrease trends in epidemiological studies.

4. Discussion

The progression and course of infectious diseases is of interest not only to epidemiologists, but also to researchers from other disciplines. The COVID-19 pandemic prompted a new application of mathematical modelling to develop new models of epidemiological dynamics (Chen, Rui, Wang, Cui, and Yin, 2020; Maier, and Brockmann, 2020).

The first prognoses of the spread of the COVID-19 pandemic were based on the conventional SEIR compartmental models and their various modifications, previously used in epidemiology. The researchers have created the following models: SEIR/SLIR (Chinazzi, Davis, Ajelli, Gioannini, Litvinova, and Merler, 2020; Kai, Goldstein, Morgunov, Nangalia, and Rotkirch, 2020), SIRD Deterministic (Fanelli, and Piazza, 2020), (Anastassopoulou, Russo, Tsakris, and Siettos, 2020), SEIRS Stochastic (Kissler, Tedijanto, Goldstein, Grad, and Lipsitch, 2020), SIR-A Deterministic (Maier and Brockmann, 2020), SEIHARD

Deterministic (Eikenberry, Mancuso, Iboi, Phan, Eikenberry, Kuang, Kostelich, and Gumel, 2020), SEIR Deterministic (Liu, Magal, Seydi, and Webb, 2020), SIRU Deterministic (Magal and Webb, 2020), (Liu, Magal, Seydi, and Webb, 2020; Liu, Magal, Seydi, and Webb, 2020), SEIIN Stochastic (Li, Pei, Chen, Song, Zhang, Yang, and Shaman, 2020), SEIPAHRF Deterministic (Ndaïrou, Area, Nieto, and Torres, 2020).

Other researchers have based their models on the Bayes method (Ganyani, Kremer, Chen, Torneri, Faes, Wallinga, and Hens, 2020; Verity, Okell, Dorigatti, Winskill, Whittaker, and Imai, 2020; Zhang, Litvinova, Wang, Wang, Deng, and Chen, 2020), the agent model (Kai, Goldstein, Morgunov, Nangalia, and Rotkirch, 2020; Koo, Cook, Park, Sun, Sun, Lim, Tam, and Dickens, 2020), the generalized growth model (Munayco, Tariq, Rothenberg, Soto-Cabezas, Reyes, and Valle, 2020) and many other modelling methods (Xiang, Jia, Chen, Guo, Shu, and Long, 2021).

Some researchers have used stochastic models to produce reliable COVID-19 forecasts. The term is used in mathematics and statistics to describe processes with elements of randomness and unpredictability. However, the available studies of epidemiological predictions were not based on technical analysis, as in the case of the research presented in this paper, but on mathematical stochastic models adopted in epidemiology (Zhang, Zeb, Hussain, and Alzahrani, 2020; Tesfaye and Satana, 2021; Li and Wei, 2022).

Zhang, Zeb, Hussain, and Alzahrani (2020) emphasised the validity of using a stochastic model. They proved that the stability of stochastic graphs indicates better performance of the stochastic model compared to the deterministic models (Zhang, Zeb, Hussain, and Alzahrani, 2020).

Tesfaye and Satana (2021) on the basis of their study concluded that, due to the dynamics of COVID-19 coronavirus disease (rapid transmission and variability of the spread rate in different environments), the use of a stochastic model performed better and provided more accurate results, compared to a deterministic approach (Tesfaye, and Satana, 2021).

Also Y. Li and Z. Wei argued for the application of mathematical stochastic models in epidemiology. They believed that this forecasting method should be supported by other types of available models used for epidemic prevention and control (Li, and Wei, 2022).

The literature on the subject does not mention the application of the stochastic oscillator in epidemiology. This paper attempts an exploratory analysis of such a possibility. It was found that the oscillator can be effective in identifying increased epidemic activity. For a 7-day forecast, %K28 had to be used, while for a 14-day forecast %K21 proved to be the most effective. For long-term forecasts: 21 days and 28 days, %K14 had the highest accuracy. For each of the periods examined (7, 14,

21, 28 days), the %D₇ signal line gave the best results. It was proved that the most effective stochastic oscillator was the slow smoothed variant with the following parameters: %K14 and %D7.

Based on his own stock market research, N. Örn argued for the greater efficiency of the slow version relative to the unsmoothed version, in line with the results of the research described in this article. He used the prices of more than five thousand shares (5120) from 2007-2019 listed on the US stock exchange. In his research, he applied the unsmoothed fast version and smoothed slow version. The unsmoothed version was not very effective due to the generation of an excessive number of signals. When the smoothed version was applied, the number of transactions decreased and the average return on investment increased (Netzén Örn, 2019).

With its ability to identify cycles, trends and turning points in time series, the stochastic oscillator enables researchers to more accurately predict changes in pandemic dynamics. It is worth noting, that despite its popularity in financial analysis, it may require careful adjustment and interpretation when applied to epidemiological data. It is always important to consider the wider context of the data and consult public health experts.

5. Conclusions

The progression of the COVID-19 pandemic resulted in the need to upgrade epidemiological methods, as the use of available conventional methods of analysing epidemiological data was associated with difficulties in rapidly predicting changes in disease spread.

This paper presents the application of a stochastic oscillator to the analysis of COVID-19 data in Poland. The results obtained demonstrate that the use of the stochastic oscillator, a type of technical analysis indicator, in epidemiology can be an effective element of a system for controlling the spread of infectious diseases. It has been shown that with the appropriate choice of parameters, oscillators can be an effective tool in predicting disease incidence trends.

The research results presented can contribute to the development of innovative tools for use in prevention, as well as in crisis management.

6. Limitations

Like other publicly available epidemiological models, the use of the stochastic oscillator has its limitations. Its use requires careful interpretation and appropriate adjustment of the coefficients for the analysis of health data. This method also does not take into account many complex factors, including social and behavioural ones. While the stochastic oscillator can be used as one of research tools, the results should be interpreted in the context of broader epidemiological analyses.

References:

- Adak, D., Majumder, A., Bairagi, N. 2021. Mathematical Perspective of COVID-19 Pandemic: Disease Extinction Criteria in Deterministic and Stochastic Models. *Chaos Solitons Fractals* 142, 110381. <https://doi.org/10.1016/j.chaos.2020.110381>.
- Anastassopoulou, C., Russo, L., Tsakris, A., Siettos, C. 2020. Data-Based Analysis, Modelling and Forecasting of the COVID-19 Outbreak. *PLoS One* 15(3), e0230405. <https://doi.org/10.1371/journal.pone.0230405>.
- Brauer, F., Castillo-Chavez, C., Feng, Z. 2019. *Mathematical Models in Epidemiology*, 1st ed., Springer-Verlag, New York.
- Chen, T.M., Rui, J., Wang, Q.P., Cui, J.A., Yin, L. 2020. A Mathematical Model for Simulating the Phase-Based Transmissibility of a Novel Coronavirus. *Infect. Dis. Poverty* 9(1), 24. <https://doi.org/10.1186/s40249-020-00640-3>.
- Chinazzi, M., Davis, J.T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S. 2020. The Effect of Travel Restrictions on the Spread of the 2019 Novel Coronavirus (COVID-19) Outbreak. *Science* 368(6489), 395-400. <https://doi.org/10.1126/science.aba9757>.
- Cucinotta, D., Vanelli, M. 2020. WHO Declares COVID-19 a Pandemic. *Acta BioMed.* 91(1), 157-160. <https://doi.org/10.23750/abm.v91i1.9397>.
- Djordjevic, J., Silva, C.J., Torres, D.F.M. 2018. A Stochastic SICA Epidemic Model for HIV Transmission. *Appl. Math. Lett.*, 84, 168-175. <https://doi.org/10.1016/j.aml.2018.05.005>.
- Eikenberry, E.S., Mancuso, M., Iboi, E., Phan, C., Eikenberry, K., Kuang, Y., Kostelich, E., Gumel, A.B. 2020. To Mask or Not to Mask: Modeling the Potential for Face Mask Use by the General Public to Curtail the COVID-19 Pandemic. *Infect. Dis. Model.* 5, 293-308. <https://doi.org/10.1016/j.idm.2020.04.001>.
- Fanelli, D., Piazza, F. 2020. Analysis and Forecast of COVID-19 Spreading in China, Italy and France. *Chaos Solitons Fractals* 134, 109761. <https://doi.org/10.1016/j.chaos.2020.109761>.
- Ganyani, T., Kremer, C., Chen, D., Torneri, A., Faes, C., Wallinga, J., Hens, N. 2020. Estimating the Generation Interval for Coronavirus Disease (COVID-19) Based on Symptom Onset Data, March 2020. *Euro Surveill.* 25(17), 2000257. <https://doi.org/10.2807/1560-7917.ES.2020.25.17.2000257>.
- Hethcote, H.W. 2000. The Mathematics of Infectious Diseases. *SIAM Rev.*, 42(4), 599-653.
- Kai, D., Goldstein, G.P., Morgunov, A., Nangalia, V., Rotkirch, A. 2020. Universal Masking Is Urgent in the COVID-19 Pandemic: SEIR and Agent-Based Models, Empirical Validation, Policy Recommendations. *arXiv Preprint arXiv:2004.13553*. <https://doi.org/10.48550/arXiv.2004.13553>.
- Kai, D., Goldstein, G.P., Morgunov, A., Nangalia, V., Rotkirch, A. 2020. Universal Masking Is Urgent in the COVID-19 Pandemic: SEIR and Agent-Based Models, Empirical Validation, Policy Recommendations. *arXiv Preprint arXiv:2004.13553*. <https://doi.org/10.48550/arXiv.2004.13553>.
- Kissler, S.M., Tedijanto, C., Goldstein, E., Grad, Y.H., Lipsitch, M. 2020. Projecting the Transmission Dynamics of SARS-CoV-2 through the Postpandemic Period. *Science* 368(6493), 860-868. <https://doi.org/10.1126/science.abb5793>.
- Koo, J.R., Cook, A.R., Park, M., Sun, Y., Sun, H., Lim, J.T., Tam, C., Dickens, B.L. 2020. Interventions to Mitigate Early Spread of SARS-CoV-2 in Singapore: A Modelling Study. *Lancet Infect. Dis.*, 20(6), 678-688.
- Lai, C.C., Shih, T.P., Ko, W.C., Tang, H.J., Hsueh, P.R. 2020. Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) and Coronavirus Disease-2019 (COVID-

- 19): The Epidemic and the Challenges. *Int. J. Antimicrob. Agents* 55(3), 105924. <https://doi.org/10.1016/j.ijantimicag.2020.105924>.
- Levin, S.A., Hallam, T.G., Gross, L.J. 2012. *Applied Mathematical Ecology*, 1st ed., Springer-Verlag, Berlin.
- Li, R., Pei, S., Chen, B., Song, Y., Zhang, T., Yang, W., Shaman, J. 2020. Substantial Undocumented Infection Facilitates the Rapid Dissemination of Novel Coronavirus (SARS-CoV-2). *Science* 368(6490), 489-493. <https://doi.org/10.1126/science.abb3221>.
- Li, Y., Wei, Z. 2022. Dynamics and Optimal Control of a Stochastic Coronavirus (COVID-19) Epidemic Model with Diffusion. *Nonlinear Dynamics* 109, 91-120. <https://doi.org/10.1007/s11071-021-06998-9>.
- Liu, Z., Magal, P., Seydi, O., Webb, G. 2020. A COVID-19 Epidemic Model with Latency Period. *Infect. Dis. Model* 5, 323-337. <https://doi.org/10.1016/j.idm.2020.03.003>.
- Liu, Z., Magal, P., Seydi, O., Webb, G. 2020. Predicting the Cumulative Number of Cases for the COVID-19 Epidemic in China from Early Data. *arXiv Preprint arXiv:2002.12298*. <https://doi.org/10.48550/arXiv.2002.12298>.
- Liu, Z., Magal, P., Seydi, O., Webb, G. 2020. Understanding Unreported Cases in the COVID-19 Epidemic Outbreak in Wuhan, China, and the Importance of Major Public Health Interventions. *Biology* 9(3), 50. <https://doi.org/10.3390/biology9030050>.
- Magal, P., Webb, G. 2020. Predicting the Number of Reported and Unreported Cases for the COVID-19 Epidemic in South Korea, Italy, France, and Germany. *MedRxiv*. <https://doi.org/10.1101/2020.03.21.20040154>.
- Maier, B.F., Brockmann, D. 2020. Effective Containment Explains Subexponential Growth in Recent Confirmed COVID-19 Cases in China. *Science* 368(6492), 742-746. <https://doi.org/10.1126/science.abb4557>.
- Maier, B.F., Brockmann, D. 2020. Effective Containment Explains Subexponential Growth in Recent Confirmed COVID-19 Cases in China. *Science* 368(6492), 742-746. <https://doi.org/10.1126/science.abb4557>.
- Munayco, C.V., Tariq, A., Rothenberg, R., Soto-Cabezas, G.G., Reyes, M.F., Valle, A. 2020. Early Transmission Dynamics of COVID-19 in a Southern Hemisphere Setting: Lima, Peru: February 29th–March 30th. *Infect. Disease Modelling* 5, 338-345.
- Murray, J.D. 2002. *Mathematical Biology I: An Introduction*, 1st ed., Springer, New York.
- Ndaïrou, F., Area, I., Nieto, J.J., Silva, C.J., Torres, D.F.M. 2018. Mathematical Modeling of Zika Disease in Pregnant Women and Newborns with Microcephaly in Brazil. *Math. Methods Appl. Sci.* 41, 8929-8941. <https://doi.org/10.1002/mma.4702>.
- Ndaïrou, F., Area, I., Nieto, J.J., Torres, D.F.M. 2020. Mathematical Modeling of COVID-19 Transmission Dynamics with a Case Study of Wuhan. *Chaos Solitons Fractals* 135, 109846. <https://doi.org/10.1016/j.chaos.2020.109846>.
- Netzén Örn, A. 2019. *The Efficiency of Financial Markets Part II: A Stochastic Oscillator Approach*, 1st ed., Umea University, Umea.
- Rachah, A., Torres, D.F.M. 2016. Dynamics and Optimal Control of Ebola Transmission. *Math. Comput. Sci.* 10, 331-342. <https://doi.org/10.1007/s11786-016-0268-y>.
- Rogalski, M. 2024. COVID-19 w Polsce. <https://lifescience.pl/covid-19/statystyki/obywatelski-projekt-michala-rogalskiego-covid-19-w-polsce/>.
- Tesfaye, A.W., Satana, T.S. 2021. Stochastic Model of the Transmission Dynamics of COVID-19 Pandemic. *Advances in Difference Equations* 457. <https://doi.org/10.1186/s13662-021-03597-1>.

- Trill, A. 2020. One World, One Health: The Novel Coronavirus COVID-19 Epidemic. *Med. Clin. (Barc.)* 154(5), 175-177. <https://doi.org/10.1016/j.medcle.2020.02.001>.
- Verity, R., Okell, L.C., Dorigatti, I., Winskill, P., Whittaker, C., Imai, N. 2020. Estimates of the Severity of COVID-19 Disease. *MedRxiv*.
<https://doi.org/10.1101/2020.03.09.20033357>.
- Walls, A.C., Park, Y.J., Tortorici, M.A., Wall, A., McGuire, A.T., Veessler, D. 2020. Structure, Function, and Antigenicity of the SARS-CoV-2 Spike Glycoprotein. *Cell* 181(2), 281-292. <https://doi.org/10.1016/j.cell.2020.02.058>.
- World Health Organization. Coronavirus Disease 2019 (COVID-19).
<https://www.who.int/emergencies/diseases/novel-coronavirus-2019>.
- World Health Organization. COVID-19 Epidemiological Update 17 May 2024.
<https://www.who.int/publications/m/item/covid-19-epidemiological-update-edition-167>.
- Wu, M., Diao, X. 2015. Technical Analysis of Three Stock Oscillators Testing MACD, RSI, and KDJ Rules in SH & SZ Stock Markets. In: *Proceedings of the 4th International Conference on Computer Science and Network Technology (ICCSNT)*, 1, 320-323. IEEE.
- Xiang, Y., Jia, Y., Chen, L., Guo, L., Shu, B., Long, E. 2021. COVID-19 Epidemic Prediction and the Impact of Public Health Interventions: A Review of COVID-19 Epidemic Models Panel. *Infect. Dis. Model*, 6, 324-342.
<https://doi.org/10.1016/j.idm.2021.01.001>.
- Zhang, J., Litvinova, M., Wang, W., Wang, Y., Deng, X., Chen, X. 2020. Evolving Epidemiology and Transmission Dynamics of Coronavirus Disease 2019 Outside Hubei Province, China: A Descriptive and Modelling Study. *Lancet Infect. Dis.* 20(7), 793-802.
- Zhang, Z., Zeb, A., Hussain, S., Alzahrani, E. 2020. Dynamics of COVID-19 Mathematical Model with Stochastic Perturbation. *Advances in Difference Equations* 451.
<https://doi.org/10.1186/s13662-020-02909-1>.