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Comparative Analysis of Continuous Transfer Function Modeling and ARMAX Models for COVID-19 Spread Prediction

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Abstract - The COVID-19 pandemic has profoundly affected global health, economies, and everyday life, highlighting the importance of precise predictive models for its spread. This paper emphasizes the use of Continuous Transfer Function models and ARMAX models to simulate and forecast the transmission dynamics of COVID-19, utilizing data from Romania. The comparative analysis between Continuous Transfer Function modelling and ARMAX models for predicting the spread of COVID-19 involves evaluating both methodologies' capabilities, strengths, and limitations. This detailed examination highlights how each approach handles the complexities of epidemiological data and their effectiveness in forecasting disease dynamics. The study utilizes data from Romania to validate and compare the two models. By analysing the transmission dynamics of COVID-19 in a specific region, the study provides concrete examples of each model's performance. The comparative analysis of Continuous Transfer Function modelling and ARMAX models for COVID-19 spread prediction offers valuable insights into the strengths and limitations of each approach. In the case of the first models excel in capturing detailed, continuous-time dynamics but require more complex data and implementation. In contrast, ARMAX models provide simpler, robust short-term forecasts using more accessible discrete-time data.

***Keywords*:** virus, COVID-19, prediction, mathematical model, continuous transfer function, simulation.

1. Introduction

The COVID-19 pandemic, caused by the novel coronavirus SARS-CoV-2, emerged in late 2019 and swiftly became a global health crisis, profoundly affecting public health systems, economies, and everyday life. SARS-CoV-2 belongs to the coronavirus family, which includes other notable viruses such as SARS-CoV (responsible for the Severe Acute Respiratory Syndrome outbreak in 2003) and MERS-CoV (responsible for the Middle East Respiratory Syndrome outbreak in 2012)[1].

The virus primarily spreads through respiratory droplets and aerosols, making it highly transmissible in various settings, from households to large gatherings. Given its rapid spread and severe impact, predicting the transmission dynamics of COVID-19 is crucial for effective public health responses and resource management.

The virus quickly spread across borders, leading to a rapid escalation in cases worldwide. By early 2020, COVID-19 had been declared a pandemic by the World Health Organization (WHO)[2].

Impact on Health and Society:

- Healthcare Systems: The pandemic strained healthcare systems worldwide, leading to overwhelmed hospitals, shortages of medical supplies, and challenges in providing adequate care to patients.
- Socioeconomic Impact: COVID-19 caused widespread disruption to economies, with millions experiencing unemployment, business closures, and financial instability[3].
- Social Distancing Measures: Governments implemented various measures, including lockdowns, social distancing guidelines, mask mandates, and travel restrictions, to mitigate the spread of the virus[4].

The prediction of COVID-19 is a multifaceted endeavour that requires a combination of scientific expertise, technological innovation, and interdisciplinary collaboration. By harnessing the power of predictive modelling, one can better understand the trajectory of the pandemic and take proactive measures to mitigate its impact on public health and society[5], [6].

2. Implementation of mathematical models

Effective COVID-19 prediction relies heavily on the quality and comprehensiveness of the data collected. This section outlines the process of gathering and processing the data needed for developing accurate predictive models, focusing on both Continuous Transfer Function and ARMAX models within a Multiple Input Single Output (MISO) system framework.

Continuous Transfer Function (CTF) models are based on systems theory and describe the relationship between inputs (e.g., infection rates, public health interventions) and outputs (e.g., number of cases) in a continuous-time framework. These models utilize differential equations to capture the real-time dynamics of disease spread, offering detailed insights into how changes in inputs affect outputs over time[7], [8].

ARMAX (AutoRegressive Moving Average with Exogenous Inputs) models operate in a discrete-time framework, combining autoregressive (AR) terms, moving average (MA) terms, and exogenous inputs (X) to predict future values of a time series[9], [10].

These models are particularly effective for short-term forecasting and incorporating external factors that influence transmission dynamics, such as weather conditions or mobility patterns.

A Multiple Input Single Output (MISO) system is a type of modelling approach where multiple input variables

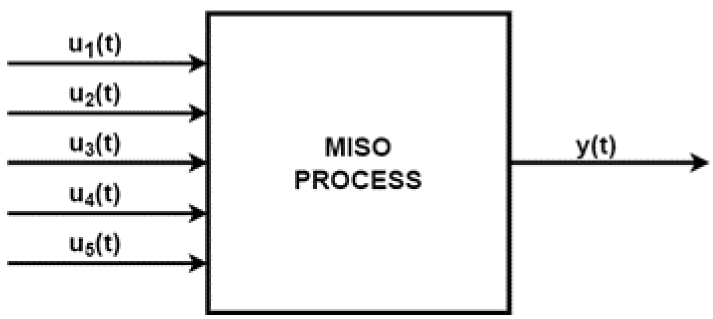

Figure 1. The MISO system

influence a single output variable.

In the context of COVID-19 prediction, a MISO system (Figure 1) can effectively capture the complex interplay between various factors that drive the transmission dynamics of the virus and predict a specific outcome, such as the number of daily new cases.

In this paper, the primary input signals include indoor and outdoor temperatures, humidity influenced by seasonal and other factors, the daily number of tests conducted, considering the reduced testing frequency on weekends, and the measures implemented by authorities in response to the total number of cases.

By meticulously collecting and processing the data, the predictive models are equipped with high-quality, comprehensive datasets that enhance their accuracy and reliability. This structured approach ensures that the models can effectively capture the complex dynamics of COVID-19 spread and provide valuable forecasts for public health planning and intervention.

The results demonstrate that both Continuous Transfer Function and ARMAX models can effectively use multiple inputs to provide accurate predictions, with Continuous Transfer Function models offering detailed continuous-time insights and ARMAX models excelling in short-term discrete-time forecasts.

Once both CTF and ARMAX models are developed, they are compared based on their predictive accuracy, computational efficiency, and suitability for specific forecasting the pandemic. The strengths and limitations of each model are carefully considered to determine which model best meets the requirements.

3. Obtained results

The comparative analysis of Continuous Transfer Function modelling and ARMAX models for predicting COVID-19 spread involves evaluating several key metrics and outcomes to determine the effectiveness of each modelling approach. Here, we delve into the specifics of the obtained results and their implications.

Both models were validated using a portion of the data set aside for testing. The predictions were compared against actual observed data to assess accuracy (Figure 2 and Figure 3).

Metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) were used to quantify predictive performance.

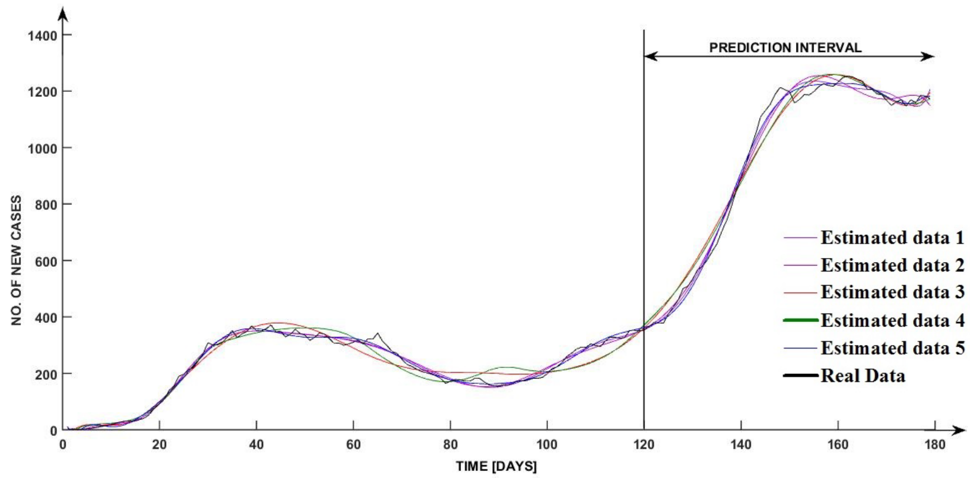

Figure 2. The representation of the transfer functions estimation versus the real data.

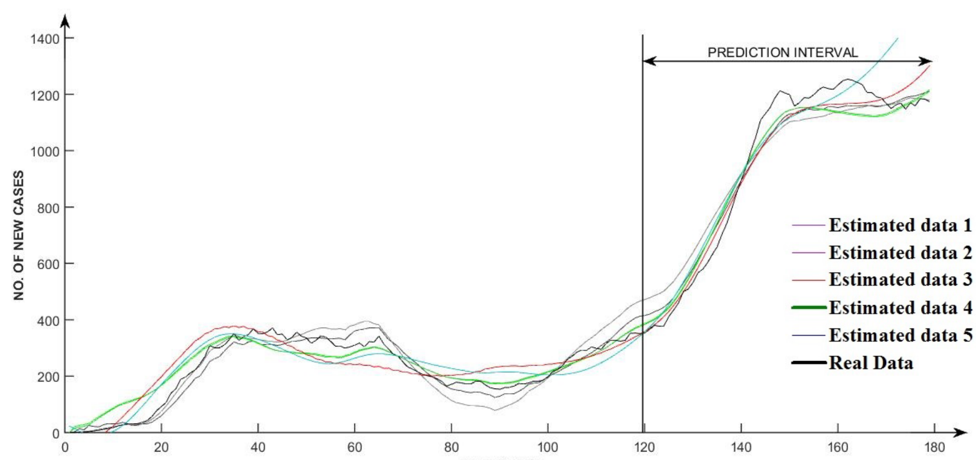

Figure 3. ARMAX-model estimated transfer functions.

4. Conclusion

Predicting the spread of COVID-19 is a critical component of the global response to the pandemic. Through modelling approaches such as Continuous Transfer Function models and ARMAX models, researchers and public health officials can gain valuable insights into the dynamics of disease transmission, optimize intervention strategies, and save lives. As the pandemic evolves, ongoing improvements in data collection, model development, and computational techniques will further enhance the accuracy and utility of COVID-19 predictions.

The main reasons why the prediction of such a pandemic is needed is because it affects some of the most important domains:

- Forecasting Disease Spread: Predictive models provide estimates of future case counts, hospitalizations, and deaths, enabling public health authorities to anticipate and prepare for potential surges in infections.
- Evaluating Interventions: Models can simulate the impact of various intervention strategies, such as lockdowns, mask mandates, and vaccination campaigns, helping policymakers decide on the most effective measures to control the spread of the virus.
- Informing Vaccine Distribution: Accurate predictions of infection hotspots and vulnerable populations guide the targeted distribution of vaccines, maximizing their impact on reducing transmission and preventing severe cases.
- Real-Time Decision Making: Continuous monitoring and updating of predictive models allow for real-time adjustments to public health strategies, ensuring a timely and effective response to emerging trends in the pandemic.

References

[1] Abigirl Mawonedzo (2023). Teaching practice efficacy for preservice student teachers under COVID-19: A case study of Chitungwiza schools. 10.35293/tetfle.v4i1.4272.

[2] Wang, Haidong & Wolock, Timothy & Carter, Austin & Nguyen, Grant & Kyu, Hmwe & Gakidou, Emmanuela & Hay, Simon & Mills, Edward & Trickey, Adam & Msemburi, William & Coates, Matthew & Mooney, Meghan & Fraser, Maya & Sligar, Amber & Salomon, Joshua & Larson, Heidi & Friedman, Joseph & Abajobir, Amanuel & Abate, Kalkidan & Murray, Christopher. (2016). Estimates of global, regional, and national incidence, prevalence, and mortality of HIV, 1980-2015: The Global Burden of Disease Study 2015. The Lancet HIV. 3. e361–e387. 10.1016/S2352-3018(16)30087-X.

[3] Sommariva, Silvia & Vamos, Cheryl & Mantzarlis, Alexios & Dao, Lillie & Tyson, Dinorah. (2018). Spreading the (Fake) News: Exploring Health Messages on Social Media and the Implications for Health Professionals Using a Case Study. American Journal of Health Education. 49. 1-10. 10.1080/19325037.2018.1473178.

[5] Santos-Lozano A, Calvo-Boyero F, López-Jiménez A, Cueto-Felgueroso C, Castillo-García A, Valenzuela PL, Arenas J, Lucia A, Martín MA; COVID-19 Hospital ’12 Octubre’ Clinical Biochemisty Study Group. Can routine laboratory variables predict survival in COVID-19? An artificial neural network-based approach. Clin Chem Lab Med. 2020 Oct 2;58(12):e299-e302. doi: 10.1515/cclm-2020-0730. PMID: 33001844.

[6] Merler S. Effects of clustered transmission on epidemic growth Comment on "Mathematical models to characterize early epidemic growth: A review" by Gerardo Chowell et al. Phys Life Rev. 2016 Sep;18:112-113. doi: 10.1016/j.plrev.2016.08.005. Epub 2016 Aug 12. PMID: 27545419.

[7] Davidson MW, Haim DA, Radin JM. Using networks to combine big data and traditional surveillance to improve influenza predictions. Nature 2015; 5:8154.

[8] Dembek, Zygmunt F, Tesema Chekol and Aiguo Wu. “Best practice assessment of disease modelling for infectious disease outbreaks.” Epidemiology and Infection 146 (2018): 1207 - 1215.

[9] WHO Coronavirus Disease (COVID-2019) Situation Reports: https://www.who.int/emergencies/diseases/novelcoronavirus-2019/situation-reports/.

[10] Chen N, Zhou M, Dong X, et al. . Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study. Lancet 2020; 395: 507–513. doi:10.1016/S0140-6736(20)30211-7.