Artificial Intelligence, Smart Topological Data Analysis and Chaos in Business Continuity Management: *The Case of COVID-19 in Birmingham Airport*

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Abstract: The latest state-of-the-art empirical methods from chaos theory have incorporated smart topological data analysis (STDA) combining chaos theory methods, topological machine learning, adaptive artificial intelligence systems, topological data analysis and fractal analysis methods for attractor reconstruction and the topological study of the dynamics, with impact on risk science and complexity research. In the current work, we apply a topological adaptive AI system to the study of Birmingham airport's air traffic dynamics, and employ topological data analysis, chaos theory methods and multifractal analysis to research the resulting dynamics. Our results show the presence of a form of stochastic chaos with a low-dimensional attractor associated with a long wave dynamics in the pre-COVID-19 period, which continues in the COVID-19 crisis and subsequent recovering around a rising trend, with the topological AI system able to adapt to the COVID-19 crisis and predict with high performance the dynamics during this period. Multifractal analysis methods, applied to the adaptive topological AI system's residuals, show that the dynamical noise affecting the chaotic attractor is multifractal, with a multifractal phase transition occurring during the COVID-19 recovery period. Implications of the methods and results for business continuity management are drawn.

Keywords: Business continuity management; VUCA; BANI; Topological AI; Smart Topological Data Analysis; Chaos Theory; Risk

1. Introduction

A new organizational context is characterized by the terms volatility, uncertainty, complexity, and ambiguity (VUCA) (Bennett and Lemoine, 2014; Sinha and Sinha, 2020). The most accurate descriptions are quick and chaotic changes, lack of standards, or the constant outdating of plans and projects (Nowacka and Rzemienniak, 2022). The VUCA environment strategically challenges organizations and individuals to achieve success (Gaule et al., 2023). VUCA clearly reflects the characteristics of the emerging world through the aspects of volatility, uncertainty, complexity, and ambiguity, as well as by responses to performing in such an environment of vision, understanding, courage, clarity, adaptability, and agility (Fuentealba et al., 2023; Gaule et al., 2023). Also, the terms brittle, anxious, nonlinear, and incomprehensible (BANI) signifies the fragility of systems, processes, or organizations to sudden disruptions, emphasizing the need for resilience (Kaplan and Mikes, 2016; Linnenluecke et al., 2020).

VUCA and BANI are essential concepts in business continuity management (BCM) and resilience (Galaitsi et al., 2023). VUCA emphasizes the need for organizations to adapt to complex environments, requiring agility and flexibility in emergency response strategies. BANI opposes rigid bureaucratic structures, which can hinder adaptive decision-making in unpredictable situations (Bennett and Lemoine, 2014). To effectively address these challenges, organizations must adopt a multifaceted approach, implementing dynamic and resilient organizational structures that enable swift decision-making and coordination while acknowledging the complex nature of crises (Hrynchak and Motuzka, 2023).

In a VUCA and BANI context, organizations need to be always prepared for the various events that may partially or totally affect their operations. For this preparation, organizations need to incorporate and keep up-to-date with new technologies in their multiple processes, such as artificial intelligence. Like this, to support business continuity management, artificial intelligence (AI) can play a strategic role in organizations, as indicated.

AI enhances risk identification and assessment and management by analysing vast data across operations, supply chain, cybersecurity, natural disasters, enabling organizations to develop effective mitigation strategies and enhance resilience (Fortunato et al., 2023; Grimwade, 2023). By recognizing patterns and trends, AI can help predict potential disruptions before they occur, allowing businesses to take proactive measures to mitigate risks (Cebulla, 2023). AI aids in data-driven decision making, enhancing strategic decision-making during crises and enhancing operational continuity by integrating BCM practices with vast dataset analysis (Xiangwei et al., 2022). AI can assist decision-makers during crisis situations by providing timely insights and recommendations based on the analysis of relevant data (Yue & Shu, 2024). AI-driven predictive analytics and scenario planning enhance business resilience by simulating scenarios and predicting disruptions, thereby enhancing organizations' contingency plans and strategies (Consilvio et al., 2024). By analysing different contingency plans and their effectiveness, organizations can better prepare for different eventualities and refine their BCM strategies accordingly (Machado et al., 2022). AI-driven analytics can enhance organizations' resilience by continuously assessing and adapting their BCM practices, based on past incidents and response efforts.

Generally speaking, AI can significantly improve business continuity management by offering advanced analytics (Tyagi, 2022), real-time monitoring, decision support, automation, and predictive capabilities, enabling organizations to anticipate, prepare plans, respond, and recover from operational disruptions. Also, AI improve organizational resilience in several keyways, as indicated: Organizational resilience encompasses various dimensions, including operational, Effective leadership, communication, innovation, financial, strategic, technological, supply chain (Kassa, 2023), and human resource resilience, all of which contribute to an organization's ability to withstand and recover from disruptions (Al-Banna et al., 2022). Overall, by integrating AI technologies with BCM practices and organizational resilience strategies, organizations can enhance their ability to anticipate, respond to, and recover from disruptions, ensuring continuity of operations and minimizing the impact on stakeholders (Soldatos, 2021).

Chaos theory, enhanced by new methods from Smart Topological Data Analysis (STDA) that integrate topological machine learning, adaptive AI and topological data analysis tools, offers powerful new technological tools for BCM, including the ability to find patterns in random-looking data, making sense of complex topological patterns in time series, identifying possible exogenous and endogenous risk sources for organizations, adapting to crises and providing solutions for dealing with dynamical changes in critical business variables, without having to specify a model, but rather, instead, uncovering the topological regularities in the temporal data for characterising that data, prediction and scenario analysis.

In the present article, we address the application of these new STDA and chaos theory's empirical methods to airport traffic dynamics prediction. We apply these methods to Birmingham airport's total instrument flight rules (IFR) movements series from 2016 to 2023, finding the presence of a form of stochastic chaos characterised by a low-dimensional attractor associated with a long wave dynamics affected by multifractal noise in the period from 2016 to 2019.

We, then, address the impact of the COVID-19 crisis on the air traffic dynamics. A critical finding is that the topological adaptive AI system is capable of predicting the series during the crisis and the subsequent recovery period with a higher performance than in the pre-COVID-19 period, we also uncover a phase transition in the multifractal spectrum of the noise affecting the chaotic dynamics during the crisis period.

In section 2, we review the main concepts and methods, in section 3, we present the main results, in section 4, we provide for an overall discussion of the relevance of the applied methods to BCM and in section 5 we present the main conclusions of the work around the main empirical results for the Birmingham airport and address the relevance of the results for future research.

2. Methods

Chaos theory initially dealt with bounded nonperiodic dynamics with sensitive dependence upon initial conditions in low-dimensional deterministic systems, leading to random-looking trajectories in nonlinear deterministic systems with a small number of degrees of freedom. The theory then grew to address both networks of nonlinear oscillators (Kaneko and Tsuda, 2001), which are high-dimensional systems, as well as systems with external dynamical noise, that is, systems that exhibit chaos in the deterministic nonlinear dynamics but are also affected by noise, this is the research field of stochastic chaos (Kapitaniak, 1990), which is of particular relevance for risk science and for dealing with VUCA since it deals with endogenous and exogenous sources of risk, including the dynamical impact of noise leading to topological changes in the system's dynamics.

The identification of chaos when one only has available a time series $y(t)$, with $t = 1,2,\ldots, T$, involves the delay embedding of this series and the subsequent research of the properties of the embedded trajectory, with the phase space trajectory described by a point $p(t) = (x(t-(d-1)h),\ldots, x(t-2h), x(t-h), x(t))$ in a d-dimensional space (Takens, 1980; Harte, 2001; Gonçalves, 2022, 2023a,b).

In general, the choice of the lag depends upon analysing the series' memory, the choice can be based on the first zero crossing of the autocorrelation function, the first zero crossing of the partial autocorrelation function or the first minimum of the mutual information. For power law chaos that is, chaos with a power law spectrum, that has a very slow decay in the autocorrelation function, the first minimum of the mutual information can lead to a too short a lag and the first zero crossing of the autocorrelation function can lead to too long a lag, due to the power law scaling associated with the chaotic attractor. In this context, the partial autocorrelation function often works better at providing for a lag reference (Gonçalves, 2023b).

For the choice of dimension and subsequent analysis of the attractor based on the application of topological machine learning, one needs to find the dimension for which the topological regularities allow for a better prediction of the target series, it is here that adaptive AI equipped with topological machine learning enters into play as a part of topological data analysis methods, this is the basis of STDA and has proven effective when dealing with emergent noisy chaotic attractors in complex systems (Gonçalves, 2022; 2023a; 2023b). This method was first introduced in (Gonçalves, 2022) to deal with chaos in the COVID-19 epidemiological series, in the case where a bifurcation occurred in the Oceania region and was subsequently employed in hospitalizations from COVID-19 (Gonçalves, 2023a) and financial volatility analysis (Gonçalves, 2023b).

The method is based on selecting the embedding dimension, from a set of dimensions, that leads to the best performance, for an adaptive artificial agent equipped with a topological machine learning unit and a sliding window for learning, in the prediction the next value of the target series from the previous phase point, in this way, one is effectively searching for the embedding that leads to the most exploitable topological order that allows the prediction of the target series (Gonçalves, 2023a,b).

The use of a topological machine learning unit is key here, since one is trying to find the embedding, from a set of embeddings, that has the strongest link between the topological structure of the reconstructed attractor and the target series' dynamics, allowing the application of further topological data analysis methods to characterise the attractor and study the main dynamics in conjunction with the topological machine learning results.

Since we will be working with a k-nearest neighbours' graph analysis, the machine learning algorithm that we work with for the dimension selection is the k-nearest neighbours' algorithm, using a sliding window for relearning and employing a grid search to both calibrate the value of k and to select the optimal embedding dimension from a set of dimensions. In this case, for each value of k, we extract the dimension that minimizes the relative error measured by the root mean squared error divided by the series' amplitude (RMSE/Amplitude). The relative error metric is useful since it allows for a comparison of the performance between the two periods under analysis (pre-COVID-19 and the COVID-19 and subsequent recovery period). The sliding window for relearning allows for the adaptation to attractor epochs as well as to possible bifurcations (Gonçalves, 2022).

After calibrating the value of k and the optimal dimension, we also apply a k-nearest neighbours' graph analysis, fixing the dimension to that obtained for the optimal pair (k,d) and calculate, for different values of k, the graph's Kolmogorov-Sinai entropy (K-S entropy) and the relative degree entropy, which is the Shannon entropy of the graph's degree distribution divided by the maximum entropy, in order to characterise the topological properties of the dynamics.

We then analyse the behaviour of the RMSE/Amplitude for the adaptive topological agent and the two entropy measures obtained for each k-nearest neighbours' graph, to find the relation between the predictability and the two graph entropy measures. In this case, we find that the increase in entropy is related to a decrease in the relative error, which means that there are topological patterns associated with the nearest neighbours' connections in the reconstructed attractor that allow for prediction.

After performing this topological analysis we report, for the optimal pair (k,d), the correlation between the adaptive topological agent's predictions and the observed values as well as the explained variance, which allows us to characterise the level of noise.

In the next step, since the nearest neighbours' algorithm can be used as noise filter, we use the agent's predictions as a noise-reduced series and estimate the Lyapunov spectrum on the resulting signal using Eckmann *et al.*'s (1986) method in order to search for markers of chaos, namely, a positive largest Lyapunov exponent, we also report the Kaplan-Yorke dimension (Kaplan and Yorke, 1979; Frederickson *et al.*, 1983), which allows for a characterisation of the noise-reduced reconstructed attractor's dimensionality. In this case, we find evidence of chaos in the airport traffic's long wave dynamics, which is captured by the adaptive topological agent.

After this analysis we turn to the noise process itself, calculating the residuals and employing multifractal detrended fluctuation analysis (MFDFA) to characterise the noise process in terms of possible multifractal signatures which is characteristic of complex turbulent dynamics (Gorjão et al., 2022).

In a multifractal process, given the q-th order moments of the variations of a variable measured at different lags s, the logarithm of the moments is a function of the logarithm of the lag s multiplied by $1+\tau(q)$, where $\tau(q)$ is the scaling function equal to $qh(q) - 1$, where $h(q)$ is the generalized Hurst exponent. While monofractal scaling is characterised by a single Hurst exponent, leading to a fixed scaling law, in multifractal scaling the Hurst exponents are a function of the order $h(q)$ (Mandelbrot, 1997).

Multifractals cannot be modelled by traditional linear time series analysis methods, which do not capture the scaling involved as addressed in Mandelbrot (1997), such scaling is associated with complex nonlinear processes not corresponding to standard independent and identically distributed noise. Stochastic chaos with multifractal scaling noise is a more complex process then an independent and identically distributed (IID) noise and a monofractal noise process.

It turns out that stochastic chaos with multifractal noise is the type of stochastic chaos that characterises the air traffic data, furthermore, we will find that there is a significant change in the multifractal scaling from the pre-COVID-19 to the COVID-19 and subsequent recovery period, with impact in risk analysis. This change is characterised by a symmetry transformation of the spectrum, which corresponds to a multifractal phase transition, a particularly relevant point when addressing the impact of the crisis on the air traffic dynamics.

Now, for the period from 2020 to 2023, we analyse the ability of the topological adaptive agent to predict the target series when the disruption from COVID-19 occurs and the subsequent process of recovery using the previously obtained embedding.

The advantage of using a machine learning method with a sliding window for relearning is that it allows for an artificial agent to adapt to a change in a process, capturing both a trend and fluctuations around this trend, without having to apply any transformation to the series. The main point, in our case, is to evaluate the impact of the crisis on the ability of an adaptive topological agent to exploit the topological information in the data, using the previously reconstructed attractor, and to adapt to the crisis period. It turns out that the predictability of the target series using the previous embedding leads to an increased and high prediction performance of the adaptive topological agent during the COVID-19 period. Which means that the exploitability of topological information for prediction increased during the COVID-19 period.

After analysing the change in performance, since in the COVID-19 period we find a linear trend and long wave dynamics around this trend which are captured by the topological adaptive agent, we detrend the agent's predictions and once more estimate the Lyapunov spectrum, finding that the long wave dynamics still shows evidence of chaos.

We also calculate the residuals and apply multifractal analysis to these residuals, allowing us to characterise the dynamics pre-crisis and during the crisis period both in terms of the main chaotic dynamics as well as in terms of the associated noise patterns.

3. Findings

In Figure 1, we show the daily Birmingham airport's total IFR movements from 2016-01-01 to 2023-12-31. As can be seen, in the pre-COVID-19 period (2016-01-01 to 2019-12-31), there is a long wave dynamics around a stationary mean with evidence of turbulence, in the period from 2020-01-01, there is a large drop in traffic due to the COVID-19 crisis and a subsequent recovery in the form of a linear increasing trend with the long wave dynamics occurring around that linear increasing trend.

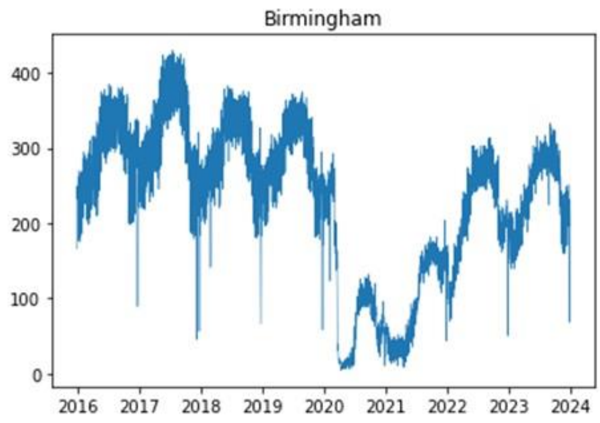

Figure 1: Daily Birmingham airport's IFR movements from 2016-01-01 to 2023-12-31.

Considering, first, the pre-COVID-19 period, in the spectral analysis (figure 2), we find that there is a power law decay associated with long range dependence and a few significant spikes which can be associated with periodic signatures, such a spectrum is consistent with a chaotic dynamics with power law scaling in the spectrum near a periodic window (onset of chaos) (Gonçalves, 2022).

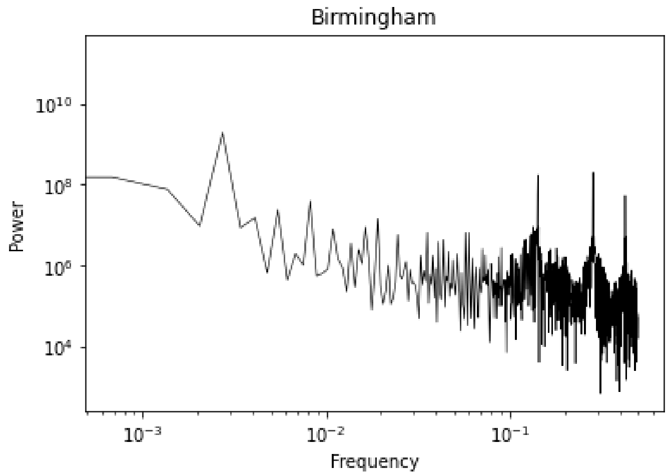

Figure 2: Power spectrum for the period from 2016-01-01 to 2019-12-31.

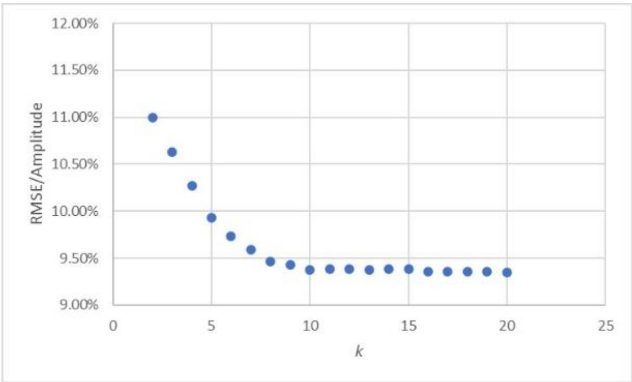

Figure 3: RMSE/Amplitude in percentage for the adaptive topological learner as a function of *k*, for the period from 2016-01-01 to 2019-12-31.

In order to select the lag for phase space reconstruction, due to the long-range dependence, we use the first zero crossing of the partial autocorrelation function, which leads to a lag of 8 days. To select the embedding dimension, in terms of exploitable topological information, we follow the previous section's described methodology and deploy an adaptive topological learner, with a *k*-nearest neighbours' learning unit, distance-based weights, KD-tree learning, sliding learning window of 30 days. We extract for different values of *k* the dimension with the lowest ratio of RMSE divided by the data amplitude. In this case, we find that, for a set of 2 to 20 dimensions, and for *k* ranging from 2 to 20, the optimal dimension is always 4, which provides strong evidence favourable a low-dimensional attractor being present in the airport's dynamics.

As shown in Figure 3, the relative error decreases with the number of nearest neighbours, converging to values below 9.4%, with the lowest value being obtained for k = 20, leading to an RMSE of 36.0028 which corresponds to an RMSE/Amplitude ratio of 9.3514%, that is, the RMSE represents 9.3514% of the total data amplitude. The correlation between the observed and predicted series is 0.7603 and the explained variance is 57.59%, which indicates the presence of noise.

The decrease in the relative error with *k* is directly related to the increase in both the degree entropy and K-S entropy of the k-nearest neighbours' graph for the reconstructed four-dimensional attractor, both these entropy measures grow with the logarithm of the number of nearest neighbours, as shown in Figure 4, which means that the rise in the topological complexity of the *k*-nearest neighbours graph with *k*, measured by the graph's entropy measures for the reconstructed attractor, leads to a rise in the predictability of the target series.

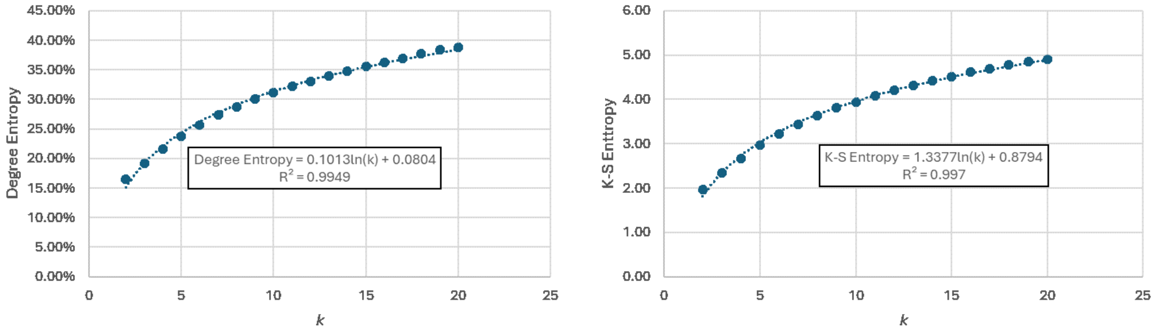

Figure 4: K-nearest neighbours graph's entropy measures as a function of the number of nearest neighbours (*k*), obtained from the embedded series, for the period from 2016-01-01 to 2019-12-31.

As shown in Figure 5 (top left), the topological learner is capable of capturing the long wave dynamics, the Lyapunov spectrum (figure 6 (right)), calculated for the predicted values (figure 6 (left)) which effectively function as a filter, shows a convergence of the spectrum with the largest Lyapunov exponent being positive and equal to 0.0017 which indicates a dynamics that is close to the onset of chaos, for the long wave dynamics. The Kaplan-Yorke dimension estimated from the Lyapunov spectrum is 1.1016 which reinforces the evidence of a chaotic attractor associated with the long wave dynamics.

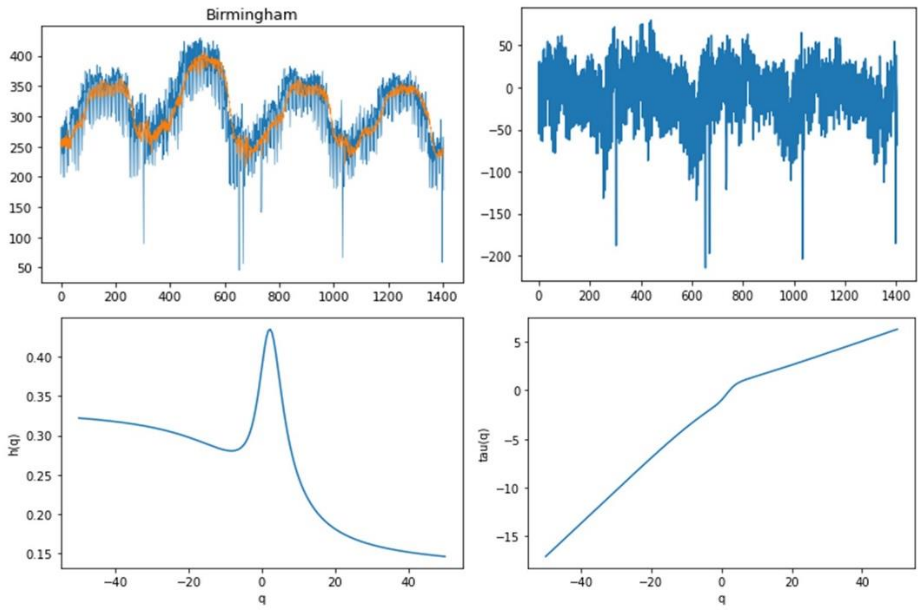

Figure 5: Observed (blue) versus predicted (orange) series for Birmingham for the period from 2016-01-01 to 2019-12-31 (top left), residual series (top right); generalized Hurst exponents' distribution for the residuals series with *q* from -50 to 50 divided by steps of 1/200, 500 lags, from 1 to 1.7, with degree 2 polynomial fit (bottom left); multifractal scaling function (bottom right).

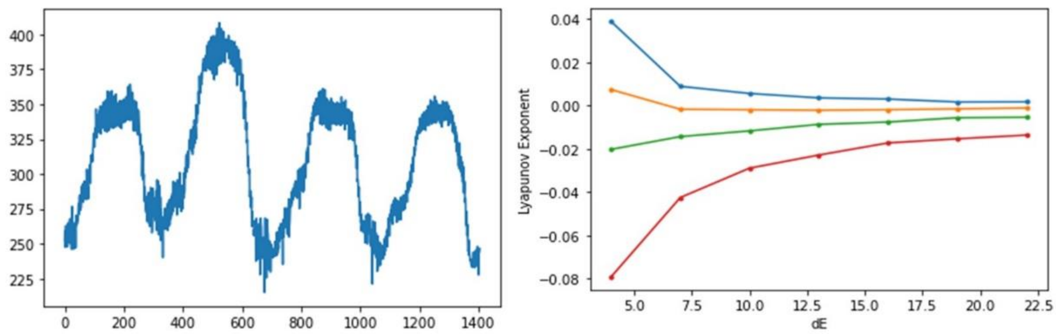

Figure 6: AI-predicted series for Birmingham for the period from 2016-01-01 to 2019-12-31 (left) and estimated Lyapunov spectrum (right) for the four-dimensional embedding of the predicted series.

The noise, in turn, which is estimated from the residuals series (Figure 5, top right) shows evidence of multifractal scaling with a wide spectrum of exponents (Figure 5, bottom left) and a scaling function that increases with the moment order, in each case a degree 2 polynomial fit was used. The estimated generalized Hurst exponents range from 0.1460 to 0.4350, with an estimated spectrum amplitude of 0.2891 for moment orders ranging from -50 to 50. The evidence is, thus, favourable to a stochastic chaotic dynamics, with a low-dimensional attractor associated with long wave dynamics, near the onset of chaos, with the stochastic component being associated with a multifractal noise process.

Now, during the COVID-19 period and subsequent recovery, the airport traffic dynamics changed, there is a large drop in the airport traffic followed by a recovery trend with the large waves occurring around the trend (Figure 7, top left).

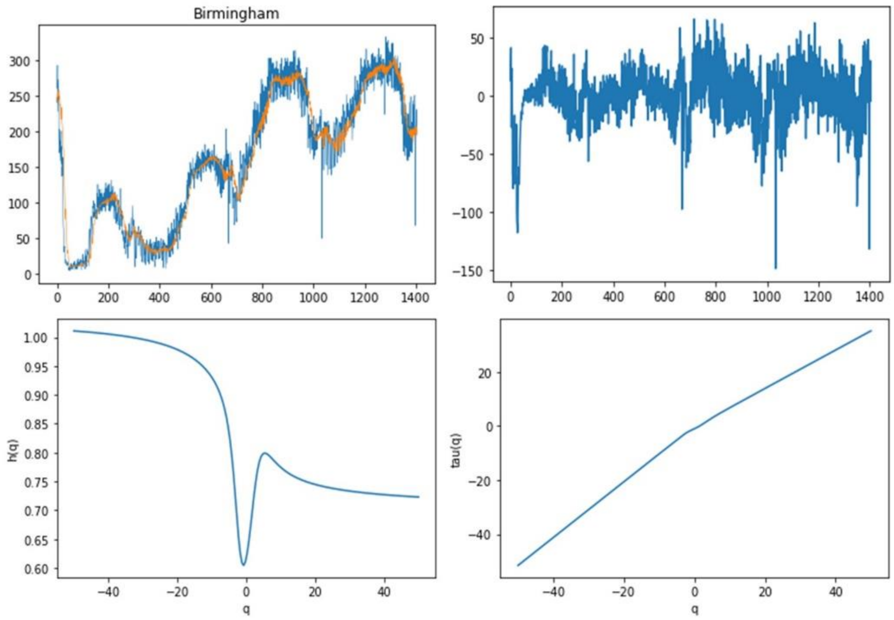

Figure 7: Observed (blue) versus predicted (orange) series for Birmingham for the period from 2020-01-01 to 2023-12-31 (top left), residual series (top right); generalized Hurst exponents' distribution for the residuals series with *q* from -50 to 50 divided by steps of 1/200, 500 lags, from 1 to 1.7, with degree 2 polynomial fit (bottom left); multifractal scaling function (bottom right).

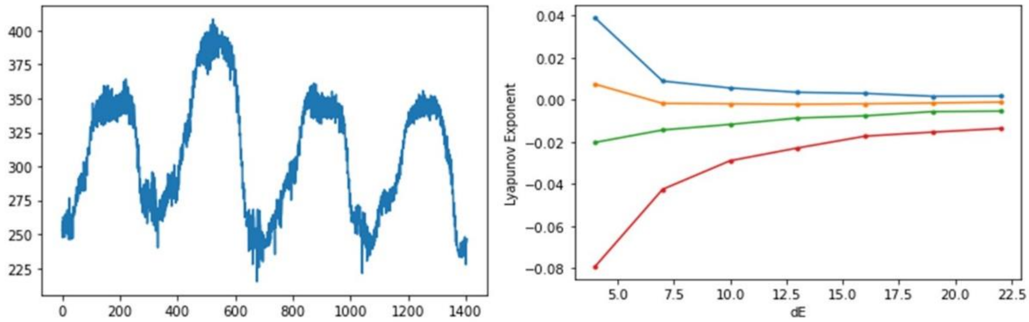

Figure 8: AI-predicted series for Birmingham for the detrended predicted series (left) for the period from 2020-01-01 to 2023-12-31 after dropping the first 100 observations in Figure 7, and estimated Lyapunov spectrum (right) for the four-dimensional embedding of the detrended predicted series.

It turns out that the adaptive topological agent, operating with the embedding parameters for the pre-COVID-19 period is able to adapt to the trend and predict the series during the crisis period with a drop in the relative error (RMSE/Amplitude) from the previous pre-COVID-19 period value of 9.3514% to 7.56%, a rise in the correlation between the observed and predicted values from 0.7603 to 0.9624 and a rise in the explained variance from 57.59% to 92.59%, which is a significant rise in predictability.

There is also a change in the noise process along the predicted trend, in this case, the noise, shown in Figure 7 (top right) is still multifractal, but there is a multifractal phase transition with the spectrum rising to higher values for the generalized Hurst exponents (Figure 7 bottom left) and there is a 180º rotation with respect to the pre-COVID-19 period, the symmetry transformation is a reflection. The scaling function still rises with the order and the estimated exponents range from 0.6045 to 1.0108, with an amplitude of 0.4063. In this way, there took place a multifractal phase transition characterised by a translation, a reflection and a dilation of the previous multifractal spectrum.

If we drop the first 100 data points which match the air traffic from the COVID-19 lockdown period we get the recovery trend, removing that linear trend we find the presence of the long wave dynamics during this recovery period (figure 8, left). Estimating the Lyapunov spectrum for the series using the previous embedding parameters, we still find a convergence of the spectrum with a positive largest Lyapunov exponent, which is indicative that the long wave dynamics along the rising recovery trend is still one of chaos, however, the largest Lyapunov exponent increased to 0.0028 and the Kaplan-Yorke dimension increased to 1.3690, which means that, while we still have a dynamics near the onset of chaos, there is a slight rise in the largest Lyapunov exponent (Figure 8, right).

4. Discussion

Chaos theory has been applied in aeronautics to address problems as diverse as air traffic flow, turbulence modelling, aircraft engineering as well as aircraft accidents (Lan, 2003; Yu and Li, 2019; Zhang *et al.*, 2020; Zhang *et al.*, 2022). In the current article, we dealt with the COVID-19 crisis impact on air traffic for the Birmingham airport, showing how STDA can be effectively applied to research the pre-crisis dynamics as well as the impact of the crisis and subsequent recovery.

Combining adaptive topological AI, chaos theory and multifractal analysis methods allows for STDA to become effective when dealing with stochastic chaos in complex systems, where emergent chaotic attractors are affected by complex noise processes (Gonçalves, 2022, 2023a,b). In this context, topological AI is a fundamental part of the analysis for embedding selection and to study the attractor's main properties when used in combination with other topological data analysis methods. STDA is robust enough to deal with bifurcations and change in attractor stability as well as the impact of large disruptive events in a system's dynamics, this later point is well-illustrated in the current article.

The insights gained from the application of STDA and chaos theory to deal with complex systems' dynamics involving business processes offers a way to gain strategic intelligence on the systems' dynamics and to reduce the strategic surprise on large events as well to gain insights for scenario analysis and to plan responses to future crises, becoming an important methodological basis for data-driven BCM.

In this context, the current work shows that topological AI is able not only to capture major properties of emergent chaotic attractors but also to adapt to disruptions and changes in dynamics associated with large impact events that may disrupt business processes offering new ground for risk science methods, theories and solutions to support BCM and in dealing with VUCA, offering a data-driven ground on which to address volatility, uncertainty, complexity, and ambiguity.

The capturing of turbulence and complex volatility patterns, the ability to reduce uncertainty especially in the context of crises, the ability to find patterns in complex dynamics and the insights offered by chaos theory's new STDA-based methods provide for a basis for understanding complex systems and reducing ambiguity through data-grounded scientific knowledge of complex systems' dynamics. In this way, the integration of topological machine learning and adaptive AI in topological data analysis methods within the context of chaos theory offers an important basis for BCM's processes, technologies and methods.

5. Conclusions

We applied smart topological data analysis (STDA) methods combining adaptive topological AI, topological data analysis, chaos theory and multifractal analysis, to study Birmingham airport's traffic dynamics and the impact of the COVID-19 crisis on that dynamics. Finding evidence of a form of stochastic chaos, characterised by a long-wave chaotic low-dimensional attractor affected by multifractal dynamical noise.

During the COVID-19 pandemic and subsequent recovery period, we found that the adaptive topological agent is capable of adapting to the crisis and predicting the subsequent dynamics. Several factors contribute to this, on the one hand, there is the predictable rising trend, on the other hand, the increase in the largest Lyapunov exponent is small and the largest Lyapunov exponent, while positive, is still, characteristic of a chaotic dynamics near the onset of chaos, the higher persistence in the noise process may have also contributed to this dynamics, because it leads to longer laminar periods in the turbulence which may have contributed to a decrease in the error.

In this way, rather than decreasing the predictability, during the crisis period and subsequent recovery the airport traffic actually became more predictable with the topological order being exploitable with the previously estimated embedding. Another important point for complexity research is that we uncovered a phase transition in the multifractal noise process during the COVID-19 crisis recovery process, characterised by a multifractal spectrum translation, dilation and reflection. The importance of the methods and findings for BCM were also addressed in the discussions' section.

The methodology and results of the present work can be extended to other airports, with impact for airport management, including the prediction of air traffic using artificially intelligent systems with adaptive learning windows and risk analysis with implications for scenario analysis, decision making technologies, data-driven business BCM, crisis management and resilience.

References

Al-Banna, A., Franzoi, R.E., Menezes, B.C., Rogers, S., and Kelly, J.D. (2022). "Roadmap to digital supply chain resilience". Computer Aided Chemical Engineering, 49, 571–576. DOI 10.1016/B978-0-323-85159-6.50095

Bennet, N., and Lemoine, J. (2014). "What VUCA really means for you". Havard Business Review, 92 (1/2)

Cebulla, A., Szpak, Z., and Knight, G. (2023). "Preparing to work with artificial intelligence: assessing WHS when using AI in the workplace". International Journal of Workplace Health Management, 16(4), 294–312. DOI 10.1108/IJWHM-09-2022-0141

Consilvio, A., Vignola, G., López Arévalo, P., Borinato, M., and Crovetto, C. (2024). "A data-driven prioritisation framework to mitigate maintenance impact on passengers during metro line operation". European Transport Research Review, 16(1), 6. DOI 10.1186/s12544-023-00631-z.

Eckmann, J.P., Kamphorst, S.O., Ruelle, D., and Ciliberto, S. (1986). "Liapunov exponents from time series". Phys Rev A Gen Phys, 34(6):4971- 4976

Fortunato, H.E., Marcomini, K., Soares, G.J., Reis, F.J., and Abbas, C. (2023). "Optimizing Industrial Risk Management Through AI and No-Code Platform: A Global Solution for the Oil and Gas Industry". Society of Petroleum Engineers - ADIPEC, ADIP 2023. DOI 10.2118/216426-MS.

Frederickson, P., Kaplan, J., Yorke, E., and Yorke, J. (1983). "The Lyapunov Dimension of Strange Attractors". J. Diff. Eqs., 49(2): 185–207.

Fuenteable, D., Flores-Fernández, C., and Carrasco, R. (2023). "VUCA bibliometric and content analysis". Revista Espanola de Documentacion Cientifica, 46(2), e354.

Galaitsi, S. E., Pinigina, E., Jeffrey, M., Pescaroli, G., Keennan, J., and Linkov, I. (2023). "Business continuity management, operational resilience, and organizational resilience: Commonalities, distinctions, and synthesis". International Journal of Disaster Risk Science, 14(5), 713–721. DOI 10.1007/s13753-023-00494-x

Gaule, E., Jovarauskiene, D., Petrauskiene, R., Pravalinskas, M., and Rauleckas, R. (2023). "Managerial approaches, frameworks, and practices for business model application in public services management in the VUCA environment". Engineering Management in Production and Services, 15(3), 84-100. doi: 10.2478/emj-2023-0022.

Gonçalves, C.P. (2022). "Low Dimensional Chaotic Attractors in SARS-CoV-2's Regional Epidemiological Data". Int J Swarm Evol Comput, 11(9): 1000271.

Gonçalves, C.P. (2023a). "Low Dimensional Chaotic Attractors in Daily Hospital Occupancy from COVID-19 in the USA and Canada". Int J Swarm Evol Comput, 12(1):1000291.

Gonçalves, C.P. (2023b). "Chaos-Induced Self-Organized Criticality in Stock Market Volatility-An Application of Smart Topological Data Analysis". Int J Swarm Evol Comput, 12:331.

Gorjão, L.R., Hassana, G., Kurths, J., and Witthauta, D. (2022). "MFDFA: Efficient multifractal detrended fluctuation analysis in python". Comp Phys Commun, 273:108254.

Grimwade, M. (2023). "The potential impacts of the digital revolution on the operational risk profiles of banks". Journal of Risk Management in Financial Institutions, 17(1), 71–88.

Harte D. (2001). Multifractals – Theory and Applications. Chapman & Hall/CRC.

Hrynchak, N., and Motuzka, O. (2023). "The key administrative competencies of managers required for company development in the bani world". Economics - Innovative and Economics Research Journal, 11(1), 289-305. doi: 10.2478/eoik-2023-0012.

Kaneko, K, and Tsuda, I. (2001). Complex systems: chaos and beyond: chaos and beyond: a constructive approach with applications in life sciences. Springer Science & Business Media.

Kapitaniak, T. (1990). Chaos in systems with noise. World Scientific.

Kaplan, J., and Yorke, J. (1979). "Chaotic behavior of multidimensional difference equations" (PDF). In Peitgen, Walther, H. O. (eds.). Functional Differential Equations and the Approximation of Fixed Points. Lecture Notes in Mathematics. Vol. 730. Springer. pp. 204–227.

Kassa, A., Kitaw, D., Stache, U., Beshah, B., and Degefu, G. (2023). "Artificial intelligence techniques for enhancing supply chain resilience: A systematic literature review, holistic framework, and future research". Computers and Industrial Engineering, 186, 109714. DOI 10.1016/j.cie.2023.109714.

Lan, L.W., Lin, F.-Y., and Kuo, A.Y. (2003). "Testing and Prediction of Traffic Flow Dynamics with Chaos", Journal of the Eastern Asia Society for Transportation Studies, Vol 5, pp 1975-1990.

Machado, R.C., Rizzi, J., Xavier, C., Chaves, V., and Oliveira, V. (2022). "Development of drill pipes failure prediction models and operational management system using real-time data analytics and AI". Proceedings of the IADC/SPE Asia Pacific Drilling Technology Conference, APDT, 2022-August. DOI 10.2118/209858-MS.

Mandelbrot B.B. (1997). "Fractals and Scaling in Finance – Discontinuity, Concentration, Risk". Springer.

Nowacka, A., and Rzemieniak, M. (2022). "The impact of the VUCA environment on the digital competences of managers in the power industry". Energies, 15, 185. https://doi.org/10.3390/en150101.

Sinha, D., and Sinha, S. (2020). "Managing in a VUCA World: Possibilities and pitfalls". Journal of Technology Management for Growing Economies, 11(1), 17–21. https://doi.org/10.15415/jtmge.2020.111003

Soldatos, J., Philpot, J., and Giunta, G. (2021). "Cyber-physical threat intelligence for critical infrastructures security: Securing critical infrastructures in air transport, water, gas, healthcare, finance and industry". Cyber-Physical Threat Intelligence for Critical Infrastructures Security: Securing Critical Infrastructures in Air Transport, Water, Gas, Healthcare, Finance and Industry, 1–443. DOI 10.1561/9781680836875.

Takens F. (1980). Detecting strange attractors in turbulence. Dynamical systems and turbulence, Springer, 366-381.

Tyagi, D.M., and Pandita, D. (2022). "Artificial intelligence and people analytics-A key to employee engagement". 2022 International Conference on Sustainable Islamic Business and Finance, SIBF 2022, 224–228. DOI 10.1109/SIBF56821.2022.9940118.

Xiangwei, K., Ziming, W., Mingzheng, W., and Xiangpei, H. (2022). "Trustworthy decision-making in artificial intelligence-enabled systems: Progress and challenges". Journal of Industrial Engineering and Engineering Management, 36(6), 1–14. DOI 10.13587/j.cnki.jieem.2022.06.001.

Yue, Y., and Shyu, J.Z. (2024). "A paradigm shift in crisis management: The nexus of AGI-driven intelligence fusion networks and blockchain trustworthiness". Journal of Contingencies and Crisis Management, 32(1), e12541. DOI 10.1111/1468-5973.12541.

Yu, H., and Li, X. (2019) "On the chaos analysis and prediction of aircraft accidents based on multi-timescales". Physica A, 534, 120828.

Zhang , Z., Zhang, A., Sun, C., Xiang, S., and Li, S. (2020). "Data-Driven Analysis of the Chaotic Characteristics of Air Traffic Flow". Journal of Advanced Transportation, 2020, 8830731.

Zhang, Z., Cui, Z., Wang, Z., and Meng, L. (2022). "Research on Chaotic Characteristics and Short-Term Prediction of En-Route Traffic Flow Using Ads-B Data". Fractals, https://doi.org/10.1142/S0218348X2340131X.