Balıkesir Medical Journal
e-ISSN: 2564-6664
B Med J 2023;7(3):117-130
DOI: 10.33716/bmedj.1415849

Modeling and Forecasting COVID-19 Incidence Rates: A Time Series Analysis of Acute Respiratory Infections (ARI) in France Since Surveillance Initiation

COVID-19 İnsidans Oranlarını Modelleme ve Öngörümleme: Fransa'da Gözetim Başlangıcından Beri Akut Solunum Enfeksiyonları (ASE) Zaman Serisi Analizi

Hanife TAYLAN SELAMLAR*
*Department of Statistics, Faculty of Science, Dokuz Eylül University, İzmir, Turkey

***Received / Geliş Tarihi:* 06.01.2024** ***Accepted / Kabul Tarihi:* 15.01.2024**

Abstract
Objective: This study aims to address the challenges of planning and managing the trajectory of the COVID-19 pandemic by evaluating the predictive abilities of three distinct forecasting models. The primary focus is on the ATA univariate forecasting method, ARIMA (AutoRegressive Integrated Moving Average), and ETS (Error-Trend-Seasonality) models. These models are applied to a meticulously collected dataset comprising Acute Respiratory Infections (ARI) incidence rates in France, systematically collected since the initiation of surveillance.
Methods: The purpose of the study was to conduct a comprehensive evaluation of forecasting models using the selected dataset to achieve its objective. The focus was on comparing the accuracy and performance of ATA univariate forecasting, ARIMA, and ETS models in predicting COVID-19 incidence rates. Additionally, the study incorporated a combination approach proven to be effective in enhancing forecasting performance.
Results: According to the results obtained regarding forecast performance, the univariate models indicate that the ATA method exhibits the highest performance, while observations reveal that combinations of ATA and ARIMA methods enhance forecast accuracy.
Conclusions: In summary, the most accurate approach for forecasting future Covid-19 incidence rates, specifically those derived from Acute Respiratory Infections (ARI), has been a combination of the high-accuracy methods ATA and ARIMA. These findings enhance our understanding of the trajectory of the pandemic, providing a foundation for strategic planning and effective management.
Keywords: Covid-19, ATAforecasting, ETS, ARIMA, Acute Respiratory Infections (ARI)

Özet
Amaç: Bu çalışma, COVID-19 pandemisinin gidişatını planlama ve yönetme zorluklarına karşı üç farklı tahmin modelinin öngörü yeteneklerini değerlendirerek ele almayı amaçlamaktadır. Temel odak noktası, ATA tek değişkenli tahmin yöntemi, ARIMA (OtoRegresif Entegre Hareketli Ortalama) ve ETS (Hata-Eğilim-Mevsimlilik) modelleridir. Bu modeller, Fransa'da gözetimin başlangıcından bu yana titizlikle toplanan Akut Solunum Enfeksiyonları (ASE) insidans oranlarını içeren bir veri setine uygulanmıştır.
Yöntem: Çalışmanın amacına ulaşmak için seçilen veri setini kullanarak tahmin modellerinin kapsamlı bir değerlendirmesini yapmak amaçlanmıştır. Odak noktası, COVID-19 insidans oranlarını tahmin etmede ATA tek değişkenli tahmin, ARIMA ve ETS modellerinin doğruluğunu ve performansını karşılaştırmaktır. Ayrıca, çalışma, tahmin performansını artırmada etkili olduğu kanıtlanmış bir kombinasyon yaklaşımını da içermiştir.
Bulgular: Tahmin performansına ilişkin elde edilen sonuçlara göre, tek değişkenli modeller, ATA yönteminin en yüksek performansı sergilediğini gösterirken gözlemler, ATA ve ARIMA yöntemlerinin kombinasyonlarının tahmin doğruluğunu artırdığını göstermektedir.
Sonuç: Özetle, gelecekteki Covid-19 insidans oranlarını, özellikle Akut Solunum Enfeksiyonları (ASE) kaynaklı olanları tahmin etmede en doğru yaklaşım, ATA ve ARIMA gibi yüksek doğrulukta yöntemlerin kombinasyonu olmuştur. Bu bulgular, pandeminin seyrine dair anlayışımızı artırarak stratejik planlama ve etkili yönetim için bir temel sağlamaktadır.
Anahtar Kelimeler: Covid-19, ATA, ETS, ARIMA, Akut Solunum Enfeksiyonları (ASE)

***Sorumlu Yazar / Corresponding Author:** Department of Statistics, Faculty of Science, Dokuz Eylül University, İzmir, Turkey. **E-mail**: hanife.taylan@deu.edu.tr

INTRODUCTION

The ongoing COVID-19 pandemic has emphasized the need for robust modeling techniques to understand its trajectory and make informed predictions. In this study, we explore the application of ATA forecasting method, ARIMA (AutoRegressive Integrated Moving Average), and ETS (Error-Trend-Seasonality) models to systematically collected Acute Respiratory Infections (ARI) incidence rates in France since the initiation of surveillance. The objective is to evaluate the forecasting capabilities of these models in estimating COVID-19 incidence rates. Effective forecasting models are essential for strategic planning and effective management of public health crises. By comparing the forecast performances of these models with actual data, this study aims to contribute valuable insights into predicting future incidence rates and enhancing our understanding of the evolving dynamics of the COVID-19 pandemic.

To enhance our understanding of forecasting methodologies, let's begin with a review of the ATA forecasting method. ATA, a straightforward and accurate statistical method, optimizes smoothing parameters and initial values simultaneously through a weighted approach based on the number of observations. Previous research has demonstrated its efficacy in improving forecast accuracy, outperforming alternatives, and showcasing superior performance in various datasets. This study proposes the Modified Simple Exponential Smoothing (MSES) method as an improved alternative to Simple Exponential Smoothing (SES), addressing its limitations for enhanced forecast accuracy, particularly evident in the M-competition's 1001 time series data [1].

In addressing the failures of Simple Exponential Smoothing, [2] compares the Ata-Simple exponential smoothing method to the standard SES. The analysis provides insights into the reasons for the failures of exponential smoothing and offers a comparative assessment of their accuracy in various forecasting scenarios. [3] introduces a modification to Holt's Linear Trend method for time series forecasting, exploring its impact on accuracy and potential advantages in capturing trends.

Introducing the ATA method for time series forecasting, [4] focuses on the additive ATA model with a linear trend component. The study highlights the single model's ability to rival alternative methods, emphasizing the substantial potential of the ATA approach.

[5] compares the ATA method to Croston-based methods for forecasting intermittent demand, and [6, 7] conducts a comparison between ATA and exponential smoothing methods on datasets with or without linear trends, demonstrating the superior performance of the proposed approach. [8] introduces an automatic time series forecasting using the ATA method, automating various stages for enhanced accessibility and simplifying the forecasting process. The fable.ata R

package serves as a modeling interface between ATAforecasting and fable, facilitating time series analysis and forecasting within the fable framework.

While ARIMA and ETS models are well-established for time series analysis, their effectiveness in modeling COVID-19 incidence rates has been explored extensively. In comparing exponential smoothing and ARIMA models, the ARIMA (0,0,2) model proves optimal for short-duration data, whereas the Holt-Winters Exponential Smoothing model exhibits greater accuracy for longer time series datasets [9]. Notably, advancements in ARIMA modeling, as exemplified by the ARIMAI model, showcase enhanced accuracy and efficiency, surpassing the capabilities of traditional ARIMA models [10].

Further contributions to the field include the development of an optimized EVDHM-ARIMA model tailored for COVID-19 forecasting, aiming to detect virus transmission rates and predict infection instances [11]. The exploration of combined approaches, such as ARIMA and ARM techniques, surfaces as a valuable strategy for COVID-19 forecasting, with the ARIMAX model incorporating ARM factors demonstrating superior predictive performance [12].

This study, in its broader scope, seeks to propose the most effective model for forecasting COVID-19 cases, shedding light on the diverse methodologies employed in recent research efforts. The evaluation of models extends to the ETS model, highlighted for its minimal Mean Absolute Percentage Error (MAPE) statistics when compared to other models [13]. The synthesis of these findings aims to provide a comprehensive understanding of the evolving landscape of COVID-19 forecasting methodologies.

Extending this methodology to France, time series analysis of ARI data has been instrumental in modeling and forecasting COVID-19 incidence rates. This comprehensive approach aims to contribute not only to accurate forecasts but also to a deeper understanding of the multifaceted dynamics surrounding COVID-19 incidence rates.

METHODS

Univariate Forecasting Method of ATA

The ATA method is an innovative forecasting technique that incorporates forms similar to exponential smoothing models. What sets ATA apart is its adaptive approach, where smoothing parameters dynamically adapt to sample size. Unlike traditional methods, ATA optimizes parameters in a discrete space, simplifying initialization. The simultaneous optimization and initialization process, with rapidly approaching zero weights for initial values, make ATA less influential, ensuring robust forecasting. ATA's universal applicability to all time series settings offers superior forecasting performance due to its inherent flexibility. In this study, the ATA method was applied to health-related data, demonstrating its positive performance and potential for broader application domains. The following paragraphs will explain the intricacies of the ATA method, including its formula and application nuances.

For a time series $\{\mathbf{y_1}, \dots, \mathbf{y_n}\}$ ATA method can be given in additive form as below:

$$\mathbf{l_t} = \left(\frac{\mathbf{p}}{\mathbf{t}}\right)\mathbf{y_t} + \left(\frac{\mathbf{t-p}}{\mathbf{t}}\right)(\mathbf{l_{t-1}} + \emptyset\mathbf{b_{t-1}}), \tag{1.1}$$

$$\mathbf{b_t} = \left(\frac{\mathbf{q}}{\mathbf{t}}\right)(\mathbf{l_t} - \mathbf{l_{t-1}}) + \left(\frac{\mathbf{t-q}}{\mathbf{t}}\right)(\emptyset\mathbf{b_{t-1}}), \tag{1.2}$$

where p is the smoothing parameter for level, q is the smoothing parameter for trend, $\emptyset$ is the dampening parameter and $l_t = y_t$ for $t \le p$, $b_t = y_t - y_{t-1}$ for $t \le q$, $b_1 = 0$, $p \in \{1,2,\dots,n\}$, $q \in \{0,1,2,\dots,p\}$, $\emptyset \in (0,1]$. Then, the h step ahead forecasts can be obtained by:

$$\hat{\mathbf{y}}_{\mathbf{t+h|t}} = \mathbf{l_t} + (\emptyset + \emptyset^{\mathbf{2}} + \dots + \emptyset^{\mathbf{h}})\mathbf{b_t}. \tag{1.3}$$

Similarly for a time series $\{y_1, \dots, y_n\}$ ATA method can be given in multiplicative form as below:

$$l_t = \left(\frac{p}{t}\right)y_t + \left(\frac{t-p}{t}\right)(l_{t-1}b_{t-1}^{\emptyset}), \tag{2.1}$$

$$\mathbf{b_t} = \left(\frac{\mathbf{q}}{\mathbf{t}}\right)\left(\frac{\mathbf{l_t}}{\mathbf{l_{t-1}}}\right) + \left(\frac{\mathbf{t-q}}{\mathbf{t}}\right)(\mathbf{b_{t-1}^{\emptyset}}), \tag{2.2}$$

where again p is the smoothing parameter for level, q is the smoothing parameter for trend, $\emptyset$ is the dampening parameter and $l_t = y_t$ for $t \le p$, $b_t = \frac{y_t}{y_{t-1}}$ for $t \le q$, $b_1 = 1$, $p \in \{1,2,\dots,n\}$, $q \in \{0,1,2,\dots,p\}, \emptyset \in (0,1]$. Then, the h step ahead forecasts can be obtained by:

$$\hat{\mathbf{y}}_{\mathbf{t+h|t}} = \mathbf{l_t} + \mathbf{b_t}^{(\emptyset+\emptyset^{\mathbf{2}}+\dots+\emptyset^{\mathbf{h}})}. \tag{2.3}$$

Since both versions of the method require three parameters we will distinguish between them by using the notation $\text{ATA}_{\text{add}}(p,q,\emptyset)$ for the additive form and $\text{ATA}_{\text{mult}}(p,q,\emptyset)$ for the multiplicative form.

Notice that when $q = 0$ both forms of ATA are reduced to the simple form $\text{ATA}(p,0,\emptyset)$ which can be written as:

$$l_t = \left(\frac{p}{t}\right)y_t + \left(\frac{t-p}{t}\right)l_{t-1}, \tag{3.1}$$

where $\mathbf{p} \in \{\mathbf{1}, \mathbf{2}, \dots, \mathbf{n}\}$ and $\mathbf{l_t} = \mathbf{y_t}$ for $\mathbf{t} \leq \mathbf{p}$. Forecasts then can be obtained by $\hat{\mathbf{y}}_{\mathbf{t+h|t}} = \mathbf{l_t}$.

To sum up, ATA can be given in different forms, namely the additive damped form $\mathrm{ATA_{add}}(\mathrm{p}, \mathrm{q}, \emptyset)$ (equations (1.1)-(1.3)), multiplicative damped form $\mathrm{ATA_{mult}}(\mathrm{p}, \mathrm{q}, \emptyset)$ (equations (2.1)-(2.3)), simple form $\mathrm{ATA}(\mathrm{p}, 0, \emptyset)$ (equation (3.1)).

ARIMA Model

The AutoRegressive Integrated Moving Average (ARIMA) model is widely used in time series analysis [14]. ARIMA assesses the relationships and trends between previous values of the existing data. The model combines three essential components: AutoRegressive (AR), Integrated (I), and Moving Average (MA) [15]. The AutoRegressive component represents the relationship between past values, while the Moving Average predicts future values through the current error terms. The Integration component determines the stationarity level in the data series [16]. By combining these components, the ARIMA model provides a robust tool for understanding time series data and predicting future values.

ETS Model

The Error-Trend-Seasonality (ETS) model is a forecasting model that takes errors, trends, and seasonality into account when making predictions [16]. The ETS model combines three fundamental components: error, trend, and seasonality [17]. The error component represents the difference between predictions and actual values. The trend component determines the overall trend in the data set. The seasonality component describes repeated patterns in a specific period [18]. By integrating these three components, the ETS model effectively analyzes time series data and predicts future values.

Modeling and Forecasting

In this study, ATA, ARIMA, and ETS forecasting methods were applied to a meticulously collected dataset of Acute Respiratory Infections (ARI) incidence rates in France since the initiation of surveillance. The weekly time series dataset, spanning from 2020 to 2023, captures the temporal dynamics of ARI, providing a rich source for modeling and forecasting the incidence rates of these respiratory infections, as illustrated in Figure 1. Each entry in the dataset corresponds to a specific time point, allowing for a comprehensive exploration of the temporal patterns and trends associated with ARI. For this exploration, the dataset was divided into test and train sets, with the last year, consisting of 52 weeks, designated as the test data. The relevant models were trained on the training portion and their performances were compared using the test data. Based on this comparison, the best-performing model, i.e., the one with the highest forecast accuracy, was used to predict the first 13 weeks of 2024.

The ARI dataset encompasses a variety of information, including regularly recorded incidence rates, potential influencing factors, and the contextual backdrop of public health interventions. The graph below illustrates instances where incidence rates show increases at specific time intervals in the given dataset. This study aims to obtain the most accurate time series method for predicting the first 13 weeks of the year 2024.

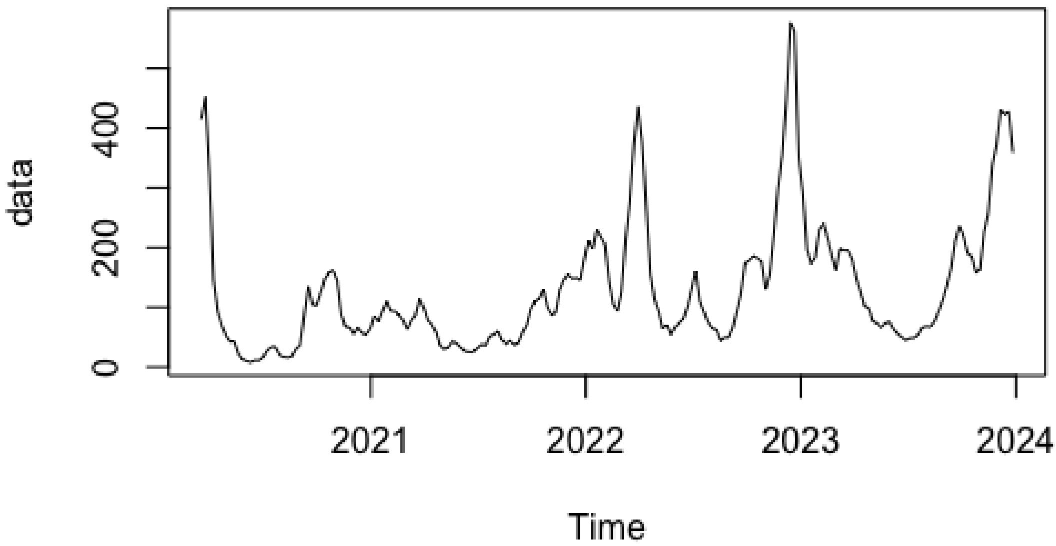

Figure 1. Incidence rate of acute respiratory infection (ARI) in France from start of surveillance (Rate per 100 000 inhabitants)

RESULTS

Table 1 illustrates the accuracy performance of the employed forecasting methods, namely ATA, ETS, and ARIMA, across various accuracy measures. Root Mean Square Error (RMSE) is a metric used to quantify the average magnitude of errors between forecasted and observed values. It is particularly useful as it squares the errors, giving more weight to larger discrepancies. On the other hand, Mean Absolute Error (MAE) provides a straightforward measure by calculating the average absolute differences between forecasted and observed values, offering insight into overall accuracy without emphasizing the size of errors.

Mean Percentage Error (MPE) takes a step further by expressing the average percentage difference between forecasted and observed values. This metric provides information on the direction and magnitude of errors, giving a sense of the overall accuracy of the model in a percentage format. Complementing this, Mean Absolute Percentage Error (MAPE) calculates the average absolute percentage differences, offering a relative measure of accuracy that is easy to interpret.

Lastly, Mean Absolute Scaled Error (MASE) compares the forecasting model's performance to a naive model, taking into account both the scale and direction of errors. This metric is valuable for assessing how well the model performs in relation to a baseline, providing a comprehensive evaluation of forecasting accuracy.

Additionally, the modeling was conducted using the fable package in the R programming language, employing an automatic time series procedure for ETS, ARIMA, and ATA models. In this context, classical decomposition was selected as the seasonal approach for ATA_seasonal, while an automatic time series forecasting procedure was utilized for ATA_full.

Table 1. Accuracy Performance of Utilized Forecasting Methods. *ME (Mean Error), RMSE (Root Mean Squared Error),MAE (Mean Absolute Error), MPE (Mean Percentage Error),MAPE (Mean Absolute Percentage Error),MASE (Mean Absolute Scaled).*

Model	Type	ME	RMSE	MAE	MPE	MAPE	MASE
arima	Test	23	116	92.9	-32.8	75.7	1.13
ata_full	Test	-40.6	**110**	**90.1**	-83.5	97.1	**1.09**
ata_seasonal	Test	-111	169	135	-95	101	1.64
ata_simple	Test	-186	213	195	-212	214	2.37
ets	Test	93.9	142	97.8	41.8	**45.3**	1.19
mixed	Test	-8.82	**106**	**86.9**	-58.1	83.9	**1.06**

The assessment of forecasting methods on the test dataset highlights notable variations in accuracy performances across different measures. Despite these differences, the performance of the ATA_full model stands out, particularly excelling when compared to other models. The combination of ARIMA and forecasting yields noteworthy results, drawing attention to the effectiveness of this tandem approach. The ARIMA model demonstrates mixed results, exhibiting a substantial mean error (ME) but relatively low root mean squared error (RMSE) and mean absolute error (MAE). The ATA_full model, despite a significant negative ME, achieves a balanced performance with comparable RMSE and MAE values. On the other hand, the ATA_seasonal and ATA_simple models show elevated errors across all measures, indicating challenges in capturing the underlying patterns in the test data. The ETS model stands out with a notably high ME but competitive RMSE and MAE values, suggesting its effectiveness in predicting the direction of the data, albeit with larger errors. Lastly, the Mixed model displays a balanced performance across all measures, reflecting its versatility in capturing diverse patterns within the test dataset.

This assessment underscores the importance of considering multiple accuracy metrics to comprehensively evaluate forecasting methods, providing researchers with nuanced insights into their respective strengths and weaknesses.

Upon examining Figure 2, it is observed that the combination of univariate models enhances forecast performance, as evidenced by the original observations, forecast values, and confidence intervals present in the chart.

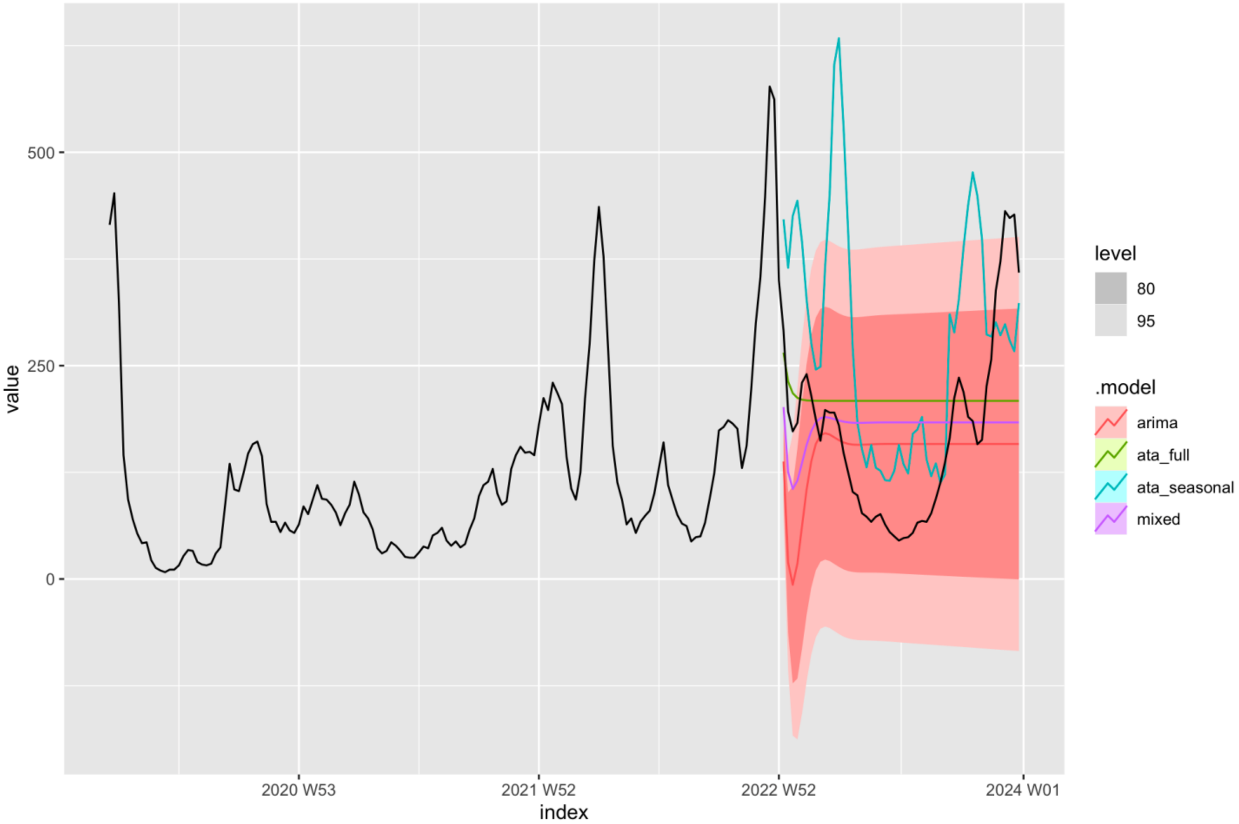

Figure 2. Forecasting Performance of Univariate Methods for Test Data (Rate per 100 000 inhabitants).

Examining Figure 3 and delving into the insights derived from Table 2, we come across a notable finding. The Ata_full model, showcasing the best solo performance, has seamlessly combined its forecasting strength with the second-best, the ARIMA model. This combination, aptly named "Mixed," cleverly blends the simple averages of forecast values from these two standout performers. The resulting combined model, supported and reinforced by existing scholarly works, stands as a testament to its improved predictive precision.

DISCUSSION

Time series forecasting of the incidence rates of ARI and COVID-19 in France faces several challenges. One challenge is the heterogeneity between regions, which highlights the need for local-level forecasts [19]. Another challenge is the non-seasonal and non-stationary nature of the pandemic, requiring specialized forecasting methods [20]. Additionally, incomplete and varying data from different hospitals can lead to misleading estimates of the real spread of the virus [21,22]. The availability of a large amount of COVID-19 related data serves as a motivation to develop mathematical models for predicting the course of the epidemic [23]. Furthermore, the complexity of the epidemic and the need to predict the peak and end of the epidemic make forecasting challenging. The application of popular univariate forecasting methods, widely recognized in the literature for their high accuracy in forecasting, and obtaining method combinations can enhance the predictions of incidence rates.

The evaluation of each forecasting model was conducted meticulously, considering key metrics such as RMSE, MAE, MAPE, and MASE. The ARIMA model exhibited commendable predictive accuracy, as indicated by its low RMSE of 116. However, a negative MPE of -32.8 suggested a tendency to consistently underestimate values. The ATA_full model emerged as a standout performer, showcasing competitive metrics with a RMSE of 110 and an impressive MAPE of 97.1. Despite its significant negative MPE of -83.5, emphasizing an underestimation trend, the model demonstrated notable effectiveness in capturing the underlying patterns. The ATA_seasonal model, while effective with a RMSE of 169 and a MAPE of 101, displayed a slightly higher MASE of 1.64, indicating room for improvement in forecasting accuracy. Notably, the ATA_simple model encountered challenges, reflected in the highest RMSE, MAPE, and MASE values, coupled with a substantial negative MPE of -212, suggesting significant difficulties in providing accurate forecasts. The ETS model exhibited reliable and scaled forecasts, characterized by a low RMSE, a favorable MAPE of 45.3, and a MASE of 1.19. Finally, the mixed model displayed a balanced performance, featuring a modest underestimation trend (-58.1), a competitive MAPE of 83.9, and a commendable MASE of 1.06. This nuanced analysis underscores the ATA_full model's noteworthy performance, particularly in the context of the MASE metric, emphasizing its effectiveness in capturing the intricate dynamics of the data.

With a keen eye on the upcoming 2024 horizon, this combined model presents its forecasted values for the first 13 weeks, thoughtfully laid out in the Mixed column of Table 2. The implications of this predictive ability suggest an expected decrease in incidence rates,

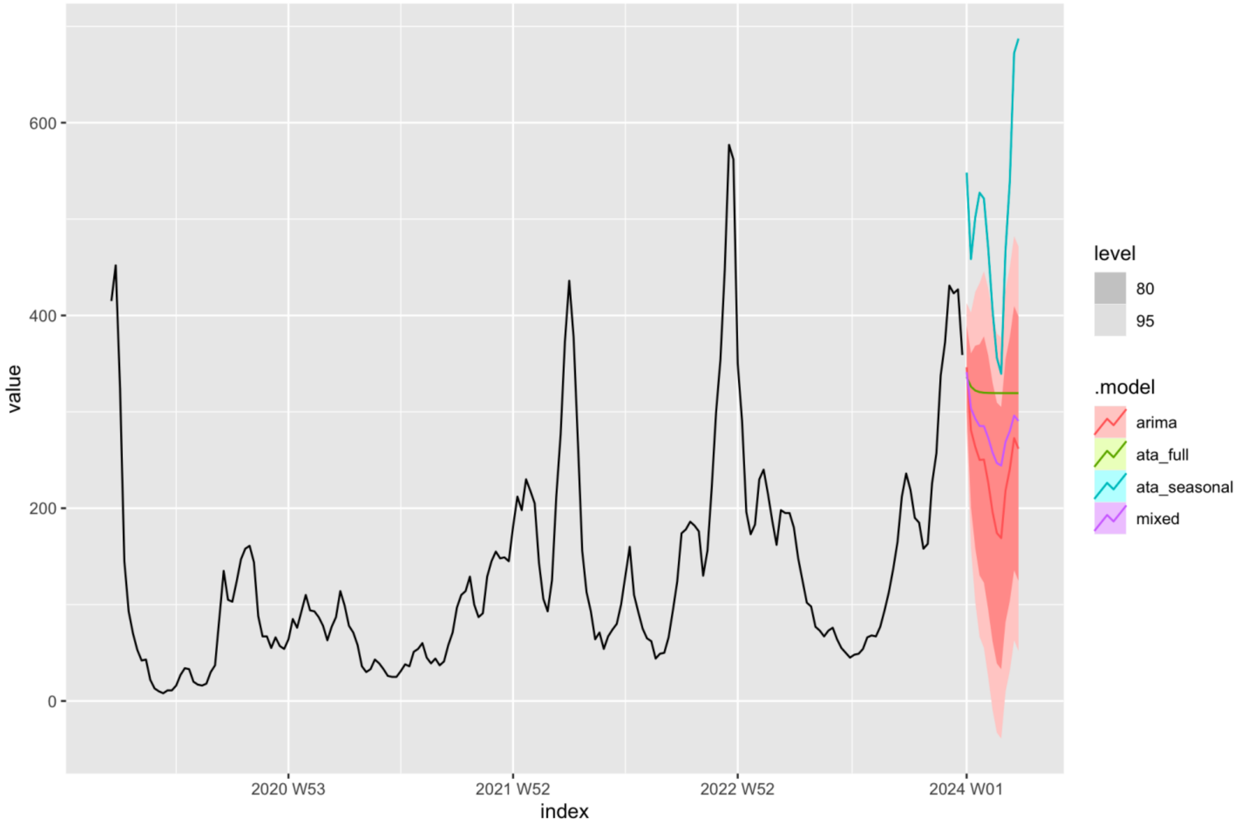

Table 2. Forecast of Covid-19 Incidence Rates of Acute Respiratory Infections (ARI) for the 13-Week Horizon in 2024 Using Different Time Series Methods (Rate per 100 000 inhabitants).

Week	ETS	ARIMA	ATA_seasonal	ATA_full	Mixed
2024 W01	340	346	548	336	**341**
2024 W02	324	281	459	326	**304**
2024 W03	312	264	502	322	**293**
2024 W04	302	250	527	320	**285**
2024 W05	294	251	521	320	**285**
2024 W06	287	227	469	320	**273**
2024 W07	282	196	406	319	**258**
2024 W08	278	174	356	319	**247**
2024 W09	275	169	339	319	**244**

2024 W10	272	218	467	319	**269**
2024 W11	270	241	539	319	**280**
2024 W12	268	273	672	319	**296**
2024 W13	267	262	687	319	**291**

In the first 13 weeks of 2024, the forecasted Covid-19 incidence rates of Acute Respiratory Infections (ARI) using different time series methods exhibit distinct values. For instance, in the ETS method for the 13th week, the forecasted rate is 267 per 100,000 inhabitants, while ARIMA forecasts it at 262. ATA_seasonal suggests a higher value of 687, ATA_full forecasts 319, and the Mixed method indicates 291. These forecasts illustrate the diverse outcomes generated by each forecasting technique. The variations in forecasts underscore the importance of selecting an appropriate forecasting model for accurate and reliable insights into the trajectory of ARI incidence rates during the 13-week period in 2024

CONCLUSION

In conclusion, this study contributes to the ongoing efforts in understanding and managing the trajectory of the COVID-19 pandemic by evaluating the predictive capabilities of the ATA univariate forecasting method, ARIMA, and ETS models. Through a meticulous analysis of Acute Respiratory Infections (ARI) incidence rates in France, spanning from 2020 to 2023, these models were applied to offer valuable insights into forecasting future incidence rates.

The comparative assessment of these forecasting models revealed diverse performances across various accuracy measures. The ATA_full model emerged as a standout performer, showcasing superior accuracy, particularly when compared to other models. The combination of ARIMA and ATA forecasting, referred to as the "Mixed" model, demonstrated noteworthy results, emphasizing the effectiveness of this combined approach.

Examining the forecasted values for the first 13 weeks of 2024, presented in Table 2, the combined model predicts a decrease in incidence rates. These findings underscore the importance of considering multiple accuracy metrics for a comprehensive evaluation of forecasting methods.

As we navigate the complex landscape of infectious disease prediction, this study emphasizes the significance of adopting versatile and robust forecasting models for strategic planning and effective management of public health crises. The insights gained from this research contribute to the evolving understanding of the dynamics surrounding COVID-19 incidence rates, providing a foundation for informed decision-making in the field of infectious disease forecasting.

Limitation

In this study, it should be noted that there is no inherent limitation to forecast due to the use of a pre-organized dataset.

Acknowledgment

The dataset used in this study belongs to a health data platform named “Sentiweb”, which serves for monitoring and analyzing various diseases in the region in Southern France. This platform facilitates the tracking of various diseases affecting public health and visualizes this data “Sentiweb” aims to provide access to health statistics for healthcare professionals, researchers, and the general public, contributing to understanding the regional health situation. I would like to express my gratitude to this organization for enabling the opportunity to contribute to my research goal.

Conflict of interest

The author declare no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

None.

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