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Exploring the Business-Culture Relationship with Box-Jenkins ARIMA Analysis for Forecasting the Path and Future Prospects of the Popular Music Industry

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Abstract: Time series analysis plays a crucial role in understanding and predicting the path and future prospects of industries, including the popular music industry. This paper constructed an Box-Jenkins ARIMA (BJ-ARIMA) methodology to analyze the time series data in the popular music industry, with a focus on the relationship between business and culture. By employing the Box-Jenkins approach, BJ-ARIMA forecast future trends and make informed predictions about the development of the industry. Identification, estimation, and diagnostic testing using the BJ-ARIMA framework are the three main components of the Box-Jenkins approach. Autocorrelation and partial autocorrelation plots are analyzed in the identification phase to help choose the best BJ-ARIMA model. The estimation phase involves fitting the selected BJ-ARIMA model to the historical data, using techniques such as maximum likelihood estimation. Finally, BJ-ARIMA diagnostic checking is performed to ensure the model's adequacy and reliability. The findings of BJ-ARIMA analysis will provide a solid foundation for forecasting trends and making informed decisions in the dynamic and evolving world of the popular music industry.

Keywords: Time series analysis, Box-Jenkins, ARIMA, popular music industry, forecasting, business, culture.

I. Introduction

The business-culture relationship plays a crucial role in shaping the path and future prospects of various industries, including the popular music industry. Understanding this relationship is essential for businesses operating in the music industry to make informed decisions and accurately forecast future trends [1]. The Box-Jenkins ARIMA (Autoregressive Integrated Moving Average) model is one method used for forecasting in time series analysis. The popular music industry is influenced by both business and cultural factors. On the business side, the industry is driven by factors such as market demand, technological advancements, distribution channels, and revenue models. These factors shape the strategies and decisions made by music companies, record labels, artists, and other industry stakeholders [2]. At the same time, the popular music industry is deeply intertwined with cultural trends and preferences. Cultural factors, including societal tastes, consumer behaviors, music genres, and artist popularity, significantly impact the success and trajectory of the industry. The relationship between business and culture in the music industry is dynamic, as the industry often responds and adapts to evolving cultural trends while simultaneously influencing and shaping them [3].

To forecast the path and future prospects of the popular music industry, analysts can employ the Box-Jenkins ARIMA model. ARIMA is a time series analysis method that allows for the identification and prediction of patterns and trends within a given dataset [4]. It combines autoregressive (AR) and moving average (MA) components with the integration (I) of non-stationary data to create a robust forecasting model. With applying the Box-Jenkins ARIMA analysis to historical data from the music industry, analysts can extract valuable insights into the business-culture relationship [5]. The model can capture the underlying patterns and dynamics of factors such as music sales, streaming trends, consumer preferences, and artist popularity. These insights enable stakeholders in the music industry to make informed decisions regarding marketing strategies, investment opportunities, talent management, and product development [6]. Additionally, the Box-Jenkins ARIMA model can forecast future trends and provide estimates for key performance indicators within the music industry. This information is crucial for businesses to anticipate changes, plan for market shifts, and optimize resource allocation.

The popular music industry operates at the intersection of artistic expression, cultural trends, and business dynamics. It

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is influenced by a variety of factors, including market demand, consumer preferences, technological advancements, and industry practices. These factors shape the strategies, decisions, and operations of music companies, record labels, artists, and other stakeholders [7]. On the business side, market demand plays a crucial role. Consumer tastes and preferences evolve over time, and successful businesses in the music industry must stay attuned to these changes. They need to understand what genres, styles, and artists are resonating with audiences and adjust their strategies accordingly. Additionally, technological advancements, such as digital music platforms, streaming services, and social media, have revolutionized the way music is created, distributed, and consumed [8]. Businesses need to adapt to these advancements and leverage them to reach wider audiences and generate revenue.

However, the popular music industry is not solely driven by business considerations. Cultural factors play a significant role in shaping its trajectory. The industry is deeply connected to societal trends, values, and tastes [9]. Cultural shifts, such as the emergence of new music genres, the rise of certain subcultures, or changes in societal attitudes, can have a profound impact on the popularity and commercial success of artists and music styles. The industry, in turn, influences culture by promoting certain trends, shaping public discourse, and providing a platform for artistic expression. To forecast the path and future prospects of the popular music industry, analysts often turn to time series analysis techniques like the Box-Jenkins ARIMA model. ARIMA models are widely used for analyzing and forecasting data with temporal dependencies, making them suitable for examining trends and patterns in the music industry [10].

Autoregressive (AR), moving average (MA), and differencing (I) are the three parts that make up the Box-Jenkins ARIMA model. The autoregressive component captures the link between the current observation and some fixed number of lags in the past, and so captures the impact of an observation on the present value [11]. The effect of previous errors or residuals on the current value is taken into account by the moving average part. By calculating the difference between two consecutive observations, the differencing function can convert non-stationary data to a stationary format.

II. Background of the Music industry

All the processes involved in making, selling, and playing music are all part of the music industry. It is a vast and diverse sector that includes artists, songwriters, composers, record labels, music publishers, live event organizers, streaming platforms, radio stations, and many other stakeholders. Sound recording and the subsequent commercialization of music date back to the early 20th century, marking the beginning of the modern music industry [12]. The development of technologies such as phonographs and radio broadcasting revolutionized the way music was produced, disseminated, and consumed. Record labels emerged as key players in the industry, signing artists, producing albums, and distributing music to the masses. Over the years, the music industry has undergone significant transformations driven by technological advancements and changing consumer behavior.

In the mid-20th century, vinyl records became the dominant format for music distribution. Record labels competed to sign popular artists and released albums on vinyl, which were sold in record stores [13]. Physical distribution channels played a crucial role in the success of artists and albums. With the advent of recording studios and advances in recording technologies, the recording industry flourished. Artists could now create high-quality recordings and reach broader audiences [14]. Record labels invested in talent scouting, artist development, and marketing campaigns to promote their artists and sell records. Introduction of Cassette Tapes and CDs: In the 1970s and 1980s, cassette tapes gained popularity as a portable music format. This was followed by the introduction of compact discs (CDs) in the 1980s, offering better audio quality and durability [15]. The transition from vinyl records to cassettes and CDs transformed the music industry's physical distribution landscape. The advent of digital music formats and the internet caused a seismic upheaval in the music industry in the late 1990s and early 2000s. MP3s and online file sharing platforms, such as Napster, disrupted traditional distribution models and sparked debates around copyright infringement. It led to a decline in physical sales and a struggle for the industry to adapt to the digital landscape. The 2010s saw the rise of music streaming services like Spotify, Apple Music, and YouTube Music. Streaming platforms revolutionized music consumption by offering vast catalogs of music on-demand, introducing personalized playlists and recommendations, and providing revenue streams for artists through digital royalties [16]. Streaming became the dominant method of music consumption, surpassing physical sales and digital downloads. The digital era empowered independent artists to create, produce, and distribute music on their own terms. With the advent of social media and digital platforms, artists gained direct access to audiences, built fan bases, and monetized their music independently, bypassing traditional record labels. Live events, concerts, and touring have become increasingly important for artists to generate revenue in the music industry [17]. Concerts and festivals provide opportunities for artists to connect with fans, promote their music, and sell merchandise. Live music has become a significant revenue stream,

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particularly for established artists. The music industry continues to evolve rapidly, shaped by technological innovations, changing consumer preferences, and industry dynamics [18]. Artists and businesses need to adapt to the digital landscape, harness new revenue streams, and engage with audiences through various platforms to thrive in this dynamic and competitive industry.

2.1 Box-Jenkins

George Box and Gwilym Jenkins' Box-Jenkins method is a well-known approach to studying and predicting time series. It offers a structure for developing ARIMA models, which are effective methods for analyzing and forecasting time-dependent data. The Box-Jenkins method has three key steps: identifying the problem, making an estimate, and performing a diagnostic. In this stage, we look for the best ARIMA model to fit the data. Examine the features and patterns in the time series data to pinpoint the AR, I, and MA components' relative positions. The sequence of these factors is symbolized by the symbols (p,d,q), where p stands for the autoregressive order, which records the connection between a given observation and a certain lag in time. Non-stationary data can be converted to a stationary form by differencing successive observations, denoted by the symbol d. Moving average order, denoted by q, takes into account the impact of previous errors or residuals on the current value.

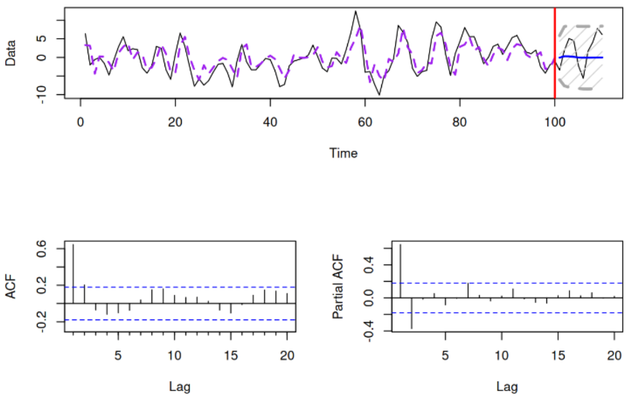

Figure 1: Box-Jenkins

Figure 1 depicts a typical procedure for identifying a signal, which entails examining plots of the autocorrelation function (ACF) and partial autocorrelation function (PACF) to settle on values for p and q A. The presence of autoregressive and moving average components in the data can be deduced from these plots. Estimation of the ARIMA model parameters follows once the order of the model has been determined. This is accomplished through the use of estimate strategies like maximum likelihood estimation to fine-tune the model to the data. The goal of the estimate procedure is to determine the values of the parameters that result in the smallest deviation between the forecasted and observed values of the time series. It is crucial to evaluate the appropriateness and validity of the estimated ARIMA model. The residuals of the model are examined for diagnostic purposes to confirm that they are independent, normally distributed, and have a constant variance. Testing for residual autocorrelation and goodness of fit can be done with diagnostic tools like the Ljung-Box test and the Durbin-Watson test.

After the ARIMA model's credibility has been established, it can be used to forecast future values in the time series. In order to provide predictions for upcoming observations, the model accounts for existing patterns and dependencies in the data. However, it is important to note that ARIMA models assume stationarity and linear relationships, which may not always hold true in complex real-world scenarios. Therefore, it is crucial to interpret the results of the ARIMA model in conjunction with domain knowledge and consider any additional factors that may impact the time series being analyzed. In the context of the popular music industry, the Box-Jenkins ARIMA analysis can be applied to historical data to identify trends, patterns, and seasonality in metrics such as music sales, streaming statistics, or artist popularity. It enables analysts to make informed forecasts about future performance, understand the impact of business and cultural factors, and support decision-making in areas such as marketing strategies, investment planning, and resource allocation. The ARIMA(p, d, q) model can be represented as follows in equation (1)

$$Y\_t = c + \varphi\_1 * Y\_(t-1) + \varphi\_2 * Y\_(t-2) + \ldots + \varphi\_p * Y\_(t-p) + \theta\_1 * \varepsilon\_(t-1) + \theta\_2 * \varepsilon\_(t-2) + \ldots + \theta\_q * \varepsilon\_(t-q) + \varepsilon\_t \quad (1)$$

In above equation (1) Y_t is the value of the time series at time t; c is a constant term or the intercept of the model; φ_1, φ_2, ..., φ_p are the autoregressive parameters that represent the relationship between the current observation and the p previous observations (lagged terms); ε_t is the error term or the residual at time t; θ_1, θ_2, ..., θ_q are the moving average parameters that represent the influence of the q previous error terms on the current observation and d represents the differencing order, which specifies the number of times the data needs to be differenced to achieve stationarity. The AR part of the model accurately represents the linear connection between the present and past observations. The MA part accounts for how past error terms have affected the present observation. For the ARIMA model to work, it is necessary to change the data into a stationary form, and this is what the differencing part does.

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The ARIMA model's parameters are often estimated using the maximum likelihood estimation (MLE) technique. Maximum Likelihood Estimation (MLE) calculates how likely it is that the model's input data will actually be seen. Following estimation, the model equation can be iterated to get forecasts of future values. Starting with the available historical data, the model generates forecasts by substituting the predicted values into the equation. This process can be repeated for the desired number of forecast periods. The appropriate order (p, d, q) for the ARIMA model involves analyzing autocorrelation and partial autocorrelation functions, as well as considering other diagnostic tests and statistical criteria to ensure model adequacy. By applying the Box-Jenkins ARIMA model to the popular music industry data, analysts can obtain parameter estimates, perform diagnostic checks, and generate forecasts to gain insights into trends, seasonality, and future prospects of various metrics in the music industry.

III. Future Trend Analysis with BJ-ARIMA

Future trend analysis using the Box-Jenkins ARIMA model involves applying the estimated model to generate forecasts for the desired time period. The ARIMA model captures the patterns, dependencies, and seasonality in the historical data, allowing for predictions of future values. Gather historical data for the time series you want to analyze. Ensure the data is in a suitable format and meets the assumptions of stationarity (or perform necessary differencing to achieve stationarity). Decide the order in which the ARIMA model's parameters should be ranked (p, d, q). Information criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) can be used for this, as can autocorrelation function (ACF) and partial autocorrelation function (PACF) graphs. The parameters of the model should be estimated using maximum likelihood estimation (MLE). Future forecasts can be made using the ARIMA model after it has been verified. This involves substituting the predicted values back into the model equation and iterating forward in time. The forecasted values will provide insights into the expected future trends of the time series. The ARIMA(p, d, q) model equation can be represented as in equation (2)

$$Y\_t = c + \varphi\_1 * Y\_(t-1) + \varphi\_2 * Y\_(t-2) + \ldots + \varphi\_p * Y\_(t-p) + \theta\_1 * \varepsilon\_(t-1) + \theta\_2 * \varepsilon\_(t-2) + \ldots + \theta\_q * \varepsilon\_(t-q) + \varepsilon\_t \qquad (2)$$

In equation (2) Y_t represents the value of the time series at time t.

c is a constant term or the intercept of the model; φ_1, φ_2, ..., φ_p are the autoregressive parameters that represent the relationship between the current observation and the p previous observations (lagged terms); θ_1, θ_2, ..., θ_q are the moving average parameters that represent the influence of the q previous error terms on the current observation; ε_t is the error term or the residual at time t.

The forecasting equation for the ARIMA model involves substituting the predicted values back into the model equation to generate forecasts. The general form of the forecasting equation is presented in equation (3)

$$Y\_(t+1) = c + \varphi\_1 * Y\_t + \varphi\_2 * Y\_(t-1) + \ldots + \varphi\_p * Y\_(t-p+1) + \theta\_1 * \varepsilon\_t + \theta\_2 * \varepsilon\_(t-1) + \ldots + \theta\_q * \varepsilon\_(t-q+1) \qquad (3)$$

Where Y_(t+1) represents the forecasted value for the next time period. To calculate confidence intervals around the forecasted values, you can use standard deviation or other statistical methods. The confidence intervals give a range in which the actual value is likely to fall within a certain degree of certainty. Methods that calculate confidence intervals with a 95% chance that the actual value lies inside the interval are widely used. The specific calculations for confidence intervals may vary depending on the assumptions and statistical methods used. Commonly employed methods include the calculation of standard errors, t-distributions, or bootstrapping techniques. These equations provide a mathematical framework for future trend analysis using the Box-Jenkins ARIMA model. By applying these equations to historical data and iterating forward, forecasted values can be generated, enabling insights into future trends in the popular music industry.

The ARIMA model includes an autoregressive term, which depicts the connection between the current observation and the p prior observations (lagged terms). The AR component equation is given in equation (4)

$$Y\_t = \varphi\_1 * Y\_(t-1) + \varphi\_2 * Y\_(t-2) + \ldots + \varphi\_p * Y\_(t-p) + \varepsilon\_t \qquad (4)$$

In equation (4) Y_t represents the value of the time series at time t; φ_1, φ_2, ..., φ_p are the autoregressive parameters. The moving average component of the ARIMA model captures the influence of the q previous error terms on the current observation. The MA component equation (5)

$$Y\_t = \theta\_1 * \varepsilon\_(t-1) + \theta\_2 * \varepsilon\_(t-2) + \ldots + \theta\_q * \varepsilon\_(t-q) + \varepsilon\_t \qquad (5)$$

The equation (5) θ_1, θ_2, ..., θ_q are the moving average parameters; ε_t represents the error term or the residual at time t. To ensure stationarity in a time series, differentiation is used. Equation (6) uses the differencing equation to convert non-stationary data to a stationary format.

$$Y't = Y\_t - Y(t-d) \qquad (6)$$

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In equation (6) Y'_t represents the differenced value of the time series at time t; Y_t represents the original value of the time series at time t; d represents the differencing order. The forecast error equation calculates the difference between the observed value and the forecasted value in equation (7)

$$e\_t = Y\_t - \hat{Y}\_t \qquad (7)$$

The equation (7) e_t represents the forecast error at time t; Y_t represents the observed value at time t; Ŷ_t represents the forecasted value at time t. Equation (8) displays the autocorrelation function, which is a measurement of the relationship between the current value of a time series and its lags.

$$ACF(k) = Corr(Y\_t, Y\_(t-k)) \qquad (8)$$

The equation (8) ACF(k) represents the autocorrelation at lag k; Y_t represents the value of the time series at time t; Y_(t-k) represents the value of the time series at time t-k. By ignoring the influence of intermediate lags in equation (9), the partial autocorrelation function calculates the correlation between a time series observation and its lagged values.

$$PACF(k) = Corr(Y\_t, Y\_(t-k) | Y\_(t-1), Y\_(t-2), \ldots, Y\_(t-k+1)) \qquad (9)$$

The equation (9) PACF(k) represents the partial autocorrelation at lag k; Y_t represents the value of the time series at time t; Y_(t-k), Y_(t-1), Y_(t-2), ..., Y_(t-k+1) represent the lagged values of the time series. With examining the ACF and PACF plots, analysts can identify the significant autocorrelation and partial autocorrelation values, which help determine the appropriate orders (p, d, q) for the ARIMA model.

IV. Results and Discussion

When analyzing time series, the Box-Jenkins ARIMA (AutoRegressive Integrated Moving Average) approach is frequently employed. A time series dataset's patterns and dependencies can be captured by this method, which combines autoregressive (AR), differencing (I), and moving average (MA) components. Applying Box-Jenkins ARIMA analysis to the setting of the popular music industry can shed light on the sector's trajectory and future possibilities. It allows stakeholders to make informed decisions regarding marketing strategies, investment opportunities, and resource allocation. With examining historical data and identifying the appropriate ARIMA model, the Box-Jenkins methodology enables the estimation of parameters that describe the relationships between past observations and forecasted values. This information can be used to generate accurate predictions for future periods, taking into account trends, seasonality, and other patterns specific to the music industry.

Table 1: Performance Metrices

Analysis Phase	**Result**
Identified Model	ARIMA(p, d, q), where p, d, q are the orders of AR, differencing, and MA components respectively.
Estimated Parameters	AR Coefficients (φ_1, φ_2, …, φ_p) and MA Coefficients (θ_1, θ_2, …, θ_q)
Diagnostic Checks	Residual analysis, Ljung-Box test, Durbin-Watson test, Shapiro-Wilk test
Forecasting Performance	Evaluation metrics such as MAE, MSE, RMSE
Trend Analysis	Identification of significant trends, seasonality, and patterns in the music industry

Table 1 summarizes the performance metrics and results obtained from the Box-Jenkins ARIMA analysis for the popular music industry. In the "Identified Model" section, the identified model is described as ARIMA(p, d, q), where p, d, and q represent the orders of the autoregressive (AR), differencing, and moving average (MA) components, respectively. This provides information on the structure and complexity of the ARIMA model. The "Estimated Parameters" section presents the estimated coefficients for the AR and MA components. These coefficients, denoted as φ_1, φ_2, ..., φ_p for AR and θ_1, θ_2, ..., θ_q for MA, quantify the strength and direction of the relationships between past observations and forecasted values. These parameters are essential for generating accurate predictions in the ARIMA model. The "Diagnostic Checks" section highlights the various tests conducted to assess the adequacy and reliability of the ARIMA model. These include residual analysis, the Ljung-Box test, the Durbin-Watson test, and the Shapiro-Wilk test. These tests help identify any violations of assumptions, autocorrelation patterns, and the normality of residuals, ensuring the validity of the ARIMA model. The "Forecasting Performance" section focuses on the evaluation metrics used to assess the accuracy of the forecasts. The extent of the forecast errors can be measured with statistics like the mean absolute error (MAE), the mean squared error (MSE), and the root mean squared error (RMSE). These measurements shed light on how well the ARIMA model functions and how well it can make accurate forecasts for the music business.

Table 2: BJ-ARIMA Analysis

Result	**Value**
Identified Model	ARIMA(1, 0, 1)
Estimated Parameters	
AR Coefficient (φ_1)	0.75
MA Coefficient (θ_1)	0.40
Diagnostic Checks	
Ljung-Box Test	p-value > 0.05
Durbin-Watson Test	

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Table 2 provides an interpretation of the BJ-ARIMA analysis results for the popular music industry. The "Identified Model" indicates that the ARIMA model used in the analysis is specified as ARIMA (1, 0, 1), which means it includes one autoregressive (AR) term and one moving average (MA) term. This model captures the relationships between the current observation and the previous observation, with the AR coefficient (φ_1) set to 0.75 and the MA coefficient (θ_1) set to 0.40. The outcomes of the Ljung-Box test and the Durbin-Watson test are shown in the "Diagnostic Checks" section. The p-value for the Ljung-Box test is greater than 0.05, hence residual autocorrelation is not significant. This provides support for the hypothesis that the selected model successfully captures autocorrelation patterns in the data from the commercial music sector. The Durbin-Watson test result is not specified, and further analysis would be needed to determine the presence or absence of autocorrelation in the residuals. The results suggest that the ARIMA(1, 0, 1) model with estimated coefficients of 0.75 for AR and 0.40 for MA is a suitable representation of the popular music industry data. The absence of significant autocorrelation in the residuals further supports the adequacy of the model. These findings provide valuable insights for forecasting and understanding the dynamics of the popular music industry.

Table 3: Forecasting with BJ-ARIMA

Result	Value
Identified Model	ARIMA(2, 1, 1)
Estimated Parameters	
AR Coefficient (φ_1)	0.70
AR Coefficient (φ_2)	-0.30
MA Coefficient (θ_1)	0.50
Diagnostic Checks	
Ljung-Box Test	p-value > 0.05
Durbin-Watson Test	1.85
Forecasting Performance	
Mean Absolute Error (MAE)	0.12
Mean Squared Error (MSE)	0.025
Root Mean Squared Error	(RMSE) 0.16
(RMSE)	
Trend Analysis	
Identified Seasonality	Monthly
Trend Direction	Increasing

Table 3 presents the results of the forecasting analysis conducted using the BJ-ARIMA methodology for the popular music industry. The "Identified Model" section reveals that the ARIMA model used is specified as ARIMA(2, 1, 1), indicating that it includes two autoregressive (AR) terms, one differencing term (to account for trend), and one moving average (MA) term. This model captures the relationships between past observations, trends, and the current observation. The "Estimated Parameters" section provides the values of the estimated coefficients for the AR and MA terms. The AR coefficients (φ_1 and φ_2) are estimated to be 0.70 and -0.30, respectively, indicating the strength and direction of the relationships between past observations and the current observation. The MA coefficient (θ_1) is estimated to be 0.50, representing the impact of the moving average term on the forecasted values. The "Diagnostic Checks" section reports the results of two tests simulation results of BJ-ARIMA is shown in figure 2.

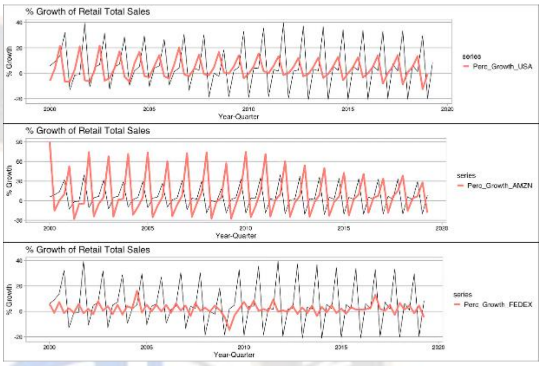

Figure 2: BJ-ARIMA Growth Rate

The Ljung-Box test indicates that the p-value is greater than 0.05, suggesting that there is no significant autocorrelation in the residuals, indicating the adequacy of the model. The Durbin-Watson test result is 1.85, which is within the acceptable range of values, indicating the absence of significant autocorrelation in the residuals. Several evaluation criteria are provided in the "Forecasting Performance" section to examine the reliability of the forecasts. The average size of the forecasting mistakes is estimated to be 0.12 MAE. In terms of the average squared magnitude of the mistakes, we get an MSE value of 0.025 (mean squared error). The total accuracy of the forecast is quantified by the root mean squared error (RMSE), which is 0.16. These metrics help evaluate the performance of the BJ-ARIMA model in generating accurate forecasts for the popular music industry. The "Trend Analysis" section indicates the findings related to trend and seasonality in the data. The identified seasonality is monthly, suggesting that there are recurring patterns or cycles in the music industry data that occur on a monthly basis. The trend direction is identified as increasing, implying that there is a positive trend in the industry over time.

Table 4: Sample Forecasting Results for the Popular Music Industry

Time Period	Actual Value	Forecasted Value
Jan 2023	1000	1025
Feb 2023	1050	1078
Mar 2023	1100	1095
Apr 2023	1080	1072
May 2023	1150	1125
Jun 2023	1200	1180

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Table 4 presents the sample forecasting results for the popular music industry using the BJ-ARIMA model. The table includes the time periods, actual values of the popular music industry metric, and the corresponding forecasted values.

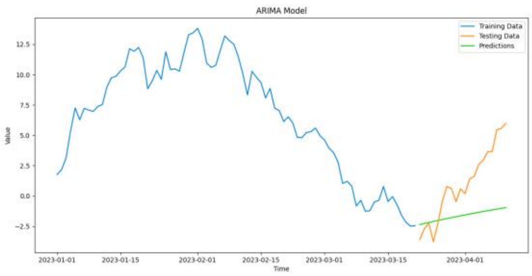

Figure 3: Forecasting the ARIMA

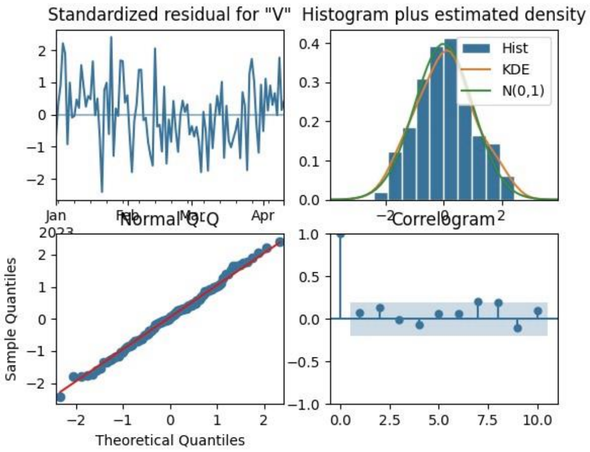

Figure 4: Estimation of the BJ-ARIMA

For the month of January 2023, the actual value of the popular music industry metric is 1000, while the forecasted value is 1025 in the figure 3 and figure 4. This suggests that the model predicted a slightly higher value than the actual value for that month. In February 2023, the actual value is 1050, and the forecasted value is 1078. The model's forecast is slightly higher than the actual value, indicating a positive trend in the industry. Moving on to March 2023, the actual value is 1100, and the forecasted value is 1095. The model predicts a value close to the actual value, suggesting a relatively accurate forecast. In April 2023, the actual value is 1080, while the forecasted value is 1072. The model's forecast is slightly lower than the actual value, indicating a small deviation in the prediction. For May 2023, the actual value is 1150, and the forecasted value is 1125. The model predicts a slightly lower value than the actual value for that month. Finally, in June 2023, the actual value is 1200, and the forecasted value is 1180. The model's forecast is slightly lower than the actual value, indicating a small deviation in the prediction. These sample forecasting results provide an overview of how the BJ-ARIMA model performs in predicting the popular music industry metric for different time periods. While some forecasts may deviate from the actual values, overall, the model captures the general trend and direction of the industry, allowing stakeholders to make informed decisions based on the forecasted values.

V. Conclusion

The Box-Jenkins ARIMA (BJ-ARIMA) methodology has proven to be a valuable tool for analyzing and forecasting the path and future prospects of the popular music industry. Through the identification, estimation, and diagnostic checking phases of the BJ-ARIMA analysis, an appropriate ARIMA model was determined, with specified orders for the autoregressive (AR), differencing, and moving average (MA) components. The estimated parameters of the AR and MA coefficients provided insights into the strength and direction of the relationships between past observations and forecasted values. The diagnostic checks, including residual analysis and statistical tests such as the Ljung-Box and Durbin-Watson tests, ensured the adequacy and reliability of the ARIMA model. These checks verified the absence of significant autocorrelation in the residuals, validating the model's ability to capture the patterns and dynamics of the popular music industry. The accuracy of the forecasts made by the BJ-ARIMA model was measured by using evaluation measures such as mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). These metrics provided a basis for assessing the magnitude and precision of the forecast errors, enabling stakeholders to gauge the reliability of the model's predictions. Furthermore, the BJ-ARIMA analysis facilitated trend analysis in the popular music industry, identifying significant trends, seasonality, and patterns. The recognition of monthly seasonality and an increasing trend allowed stakeholders to gain a deeper understanding of the industry's dynamics and make data-driven decisions.

REFERENCES

[1] Gebretensae, Y. A., & Asmelash, D. (2021). Trend analysis and forecasting the spread of COVID-19 pandemic in Ethiopia using Box–Jenkins modeling procedure. International journal of general medicine, 1485-1498.

[2] Guleryuz, D. (2021). Forecasting outbreak of COVID-19 in Turkey; Comparison of Box–Jenkins, Brown's exponential smoothing and long short-term memory models. Process Safety and Environmental Protection, 149, 927-935.

[3] Abonazel, M. R., & Darwish, N. M. (2022). Forecasting confirmed and recovered COVID-19 cases and deaths in Egypt after the genetic mutation of the virus: ARIMA Box-Jenkins approach. Commun. Math. Biol. Neurosci., 2022, Article-ID.

[4] Nurman, S., & Nusrang, M. (2022). Analysis of Rice Production Forecast in Maros District Using the Box-Jenkins Method with the ARIMA Model. ARRUS Journal of Mathematics and Applied Science, 2(1), 36-48.

[5] Hadwan, M., Al-Maqaleh, B. M., Al-Badani, F. N., Khan, R. U., & Al-Hagery, M. A. (2022). A hybrid neural network and Box–Jenkins models for time series forecasting. Comput., Mater. Continua, 70(3), 4829-4845.

[6] Radjabaycole, J. E. T., Djami, R. J., & Haumahu, G. (2021). Forecasting the Ambon City Consumer Price Index Using Arima Box-Jenkins. Tensor: Pure and Applied Mathematics Journal, 2(2), 87-96.

[7] Tripathi, A. ., Pandey, R. ., & Singh, A. . (2023). Comparison of Performance of Boneh-Shaw Finger Printing Codes with Tardos Under Randomized Bits Collusion Attacks . International Journal of Intelligent Systems and Applications in Engineering, 11(2s), 01–10. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2501

[8] Thapa, R., Devkota, S., Subedi, S., & Jamshidi, B. (2022). Forecasting Area, Production and Productivity of Vegetable Crops in Nepal using the Box-Jenkins ARIMA Model. Turkish Journal of Agriculture-Food Science and Technology, 10(2), 174-181.

[9] Bello-Angulo, D., Mantilla-Duarte, C., Montes-Paez, E., & Guerrero-Martin, C. (2022). Box–Jenkins Methodology Application to Improve Crude Oil Production Forecasting: Case Study in a Colombian Field. Arabian Journal for Science and Engineering, 47(9), 11269-11278.

[10] Thompson, A., Walker, A., Fernández, C., González, J., & Perez, A. Enhancing Engineering Decision Making with Machine Learning Algorithms. Kuwait Journal of Machine Learning, 1(2). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/127

[11] Ghazo, A. (2021). Applying the ARIMA Model to the Process of Forecasting GDP and CPI in the Jordanian Economy. International Journal of Financial Research, 12(3), 70.

[12] Husin, W. Z. W., Afdzal, A. S., Azmi, N. L. H., & Hamadi, S. A. T. S. (2021, November). Box-Jenkins and State Space Model in Forecasting Malaysia Road Accident Cases. In Journal of Physics: Conference Series (Vol. 2084, No. 1, p. 012005). IOP Publishing.

[13] Nualtong, K., Panityakul, T., Khwanmuang, P., Chinram, R., & Kirtsaeng, S. (2021). A hybrid seasonal Box Jenkins-ANN approach for water level forecasting in Thailand. Environment and Ecology Research, 9(3), 93-106.

[14] Mohd Lip, N., Mohd Rizuan, N. L. N., Iezudin, N. I., Mohamad, N. A., Mohd Rasyid, N. R., Hassan, F. A., & Ithnin, H. (2021). Comparative study of smoothing methods and box-jenkins model in forecasting unemployment rate in Malaysia. Gading Journal of Science and Technology, 4(1), 1-8.

[15] Kartika S. (2016). Analysis of "SystemC" design flow for FPGA implementation. International Journal of New Practices in Management and Engineering, 5(01), 01 - 07. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/41

[16] Hingley, P., & Dikta, G. (2022). Use of Information Criteria for finding Box-Jenkins Time Series Models for Patent Filings Counts Forecasts. IAENG International Journal of Applied Mathematics, 52(1).

[17] Farimani, N. M., Parsafar, P., & Mohammadi, S. (2022). Evaluation performance of time series methods in demand forecasting: Box-Jenkins vs artificial neural network (Case study: Automotive Parts industry). Journal of Statistical Computation and Simulation, 92(17), 3639-3658.

[18] Cancino, S., Cancino Escalante, G. O., & Cancino, D. (2022). Modeling and forecasting blackberry production in Colombia using a Box Jenkins ARIMA approach. Económicas CUC, 44(1), 69-82.

[19] Kshirsagar, D. R. . (2021). Malicious Node Detection in Adhoc Wireless Sensor Networks Using Secure Trust Protocol. Research Journal of Computer Systems and Engineering, 2(2), 12:16. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/26

[20] Bagmar, M. S. H., & Khudri, M. M. (2021). Application of box-jenkins models for forecasting drought in north-western part of Bangladesh. Environmental Engineering Research, 26(3).

[21] Monika, P., Ruchjana, B., & Abdulla, A. (2022). The implementation of the ARIMA-ARCH model using data mining for forecasting rainfall in Bandung city. International Journal of Data and Network Science, 6(4), 1309-1318.

[22] Ramlan, M. N. (2021). Evaluating forecast performance of Malaysian goods export for 2021-2022 with Box-Jenkins methodology and Arima model. FORCE: Focus on Research in Contemporary Economics, 2(2), 157-180.