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Enhancing Sustainable Dairy Industry Growth through Cold-Supply-Chain-Integrated Production Forecasting

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Abstract: Cold supply chains (CSCs) are critical for preserving the quality and safety of perishable products like milk, which plays a vital role in the daily lives of a vast population, especially in countries like India. This research centers on sustainable milk production in Northern India, with priorities of ensuring efficiency and waste reduction within the cold supply chain. Leveraging data from a prominent North India-based dairy company, Company 'X', an ARIMA model is applied for predicting monthly milk production trends. Utilizing the Statistical Package for the Social Sciences (IBM SPSS STATISTICS 20) software, the study forecasts Company 'X's monthly milk production and identifies four distinct ARIMA models based on the autocorrelation function (ACF) and the partial autocorrelation function (PACF). By comparing predicted and actual milk production values (April–October 2021), sustainability metrics are integrated into ARIMA forecasts. Implications for the dairy sector's sustainability and alignment with the Sustainable Development Goals (SDGs) are assessed through error terms such as R squared (R^2) and mean absolute percentage error (MAPE). The study promotes sustainable milk production practices in Northern India's dairy sector, resonating with the SDGs to optimize demand–supply dynamics and foster a more environmentally conscious dairy industry.

Keywords: cold supply chain; time-series analysis; ARIMA; forecasting; milk production forecasting; SPSS; SDGs; sustainability

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1. Introduction

In the context of dairy production, particularly within a significant country like India, CSCs assume a pivotal role of utmost importance. Dairy products hold a fundamental place in daily life, as they contribute to more than 10% of the body's protein requirement [1]. Throughout history, these products have evolved from being considered luxuries to becoming absolute necessities. Among these dairy products, milk stands out as a natural food source that provides all the essential nutrients required for bodily growth and development [2]. The dairy sector serves as a cornerstone for the social and economic progress of the nation, representing a substantial portion of the rural population [3,4]. Globally, India holds the top position when it comes to both the production and consumption of milk, boasting a dairy cow population of 125.34 million [5–7]. In the last ten years, India has witnessed a remarkable increase of 237.58% in milk production, soaring from 55.6 million tonnes in 1991–1992 to a remarkable 187.7 million tonnes in 2018–2019 [8]. This consistent growth has averaged around 4.8% annually in the last ten years [9,10]. Simultaneously, the daily per capita milk availability in India has risen from 130 g in 1950–1951 to 374 g in 2017, surpassing the estimated global average consumption for 2017 [11–13]. In fact, in 2017, India accounted for an impressive 21.29 % share of global milk production [14]. Since dairy accounts for one of the largest portions of agriculture's gross domestic product (GDP), it is essential to predict milk production in order to gauge supply and demand for milk and to develop the best course of action for addressing any ensuing gaps [8,15,16]. Moreover, in the dairy industry, where maintaining the integrity of CSCs is paramount, accurate predictions of milk production take on added significance. These forecasts empower stakeholders to make informed decisions that are crucial for the efficient allocation of resources and the optimization of procurement and distribution processes, especially within cold supply chains. Beyond their logistical importance, milk and dairy products are vital sources of nutrition, being rich in essential elements such as proteins, vitamins, and minerals, all of which are fundamental for human growth and development. Ensuring sustainable milk production practices is not only a matter of meeting the surging demand for dairy products but also safeguarding the environment and our precious natural resources [17]. The dairy industry's sustainability hinges on optimizing production processes, reducing environmental impact, and promoting responsible consumption and production practices [18,19]. Efficient forecasting of milk production aligns with these sustainability goals by preventing food shortages, minimizing wastage, and reducing the industry's ecological footprint [20]. The link between milk production forecasting and the SDGs further accentuates its significance. The SDGs encompass a set of global objectives aimed at eradicating poverty, protecting the planet, and ensuring prosperity for all by 2030. Sustainable milk production directly supports several SDGs, primarily within the scopes of SDG 2 ("Zero Hunger") and SDG 12 ("Responsible Consumption and Production") [21].

In light of this context, this study makes an effort to examine and predict milk production using the established time-series modelling approach ARIMA. The effectiveness of ARIMA models in forecasting milk production is evaluated based on the MAPE and the coefficient of determination (R^2). The MAPE quantifies the average percentage deviation between the predicted and actual values which reflects the precision and accuracy of the forecasting models [22,23]. A lower MAPE indicates higher forecast accuracy, with a smaller average deviation from the actual values. On the other hand, R^2 quantifies the proportion of total variation in milk production, explained by the independent variables included in the ARIMA model [24]. A higher R^2 value denotes a more robust correlation and a better fit of the model to the data, enhancing their predictive power. Through an investigation of MAPE and R^2 values, the paper aims to offer insights into the predictive competences of the ARIMA models and their ability to capture underlying patterns and trends in milk production data to facilitate sustainable decision making, hence assisting us in achieving the SDGs. To achieve this aim, the following research objectives (ROs) were identified:

- RO1: Examine the monthly milk production trends of Company 'X' in North India from April 2010 to October 2021, and identify underlying patterns and trends.
- RO2: Develop ARIMA models for forecasting milk production from April 2021 to October 2021, and evaluate the precision of the forecasted values using MAPE and R^2.
- RO3: Evaluate the implications of precise milk production forecasting for achieving SDGs in the dairy industry.

In this study, we introduce several innovative elements that constitute the core contributions of this research. First and foremost, the study pioneers the integration of CSC dynamics into the realm of milk production forecasting. While prior studies have primarily focused on predicting milk production trends, this research takes a holistic approach by considering the intricate dynamics of the CSC. This innovation allows us not only to generate accurate forecasts but also to evaluate the broader implications of these forecasts in the context of sustainability within the dairy industry. Furthermore, our study extends the conventional time-series forecasting paradigm by aligning our predictions with the SDGs. This unique approach enables us to assess the long-term impact of milk production forecasting on sustainability objectives. The study also emphasizes the crucial role of data-driven decision making in CSC management, empowering stakeholders to make informed choices about resource allocation and distribution processes. Additionally, it sheds light on the significance of strategic preparedness to mitigate the effects of unforeseen disruptions, such as the COVID-19 pandemic, on milk production forecasts.

The following is the structure of the paper: Section 2 contains the method and materials followed by the model formation in Section 3. Subsequently, Section 4 contains the results and discussions, implications, and limitations. Eventually, the paper concludes with future insights in Section 5.

2. Materials and Methods

Forecasting is a method that utilizes historical data as inputs to generate educated estimates that can be used to make accurate predictions about the trajectory of future trends [25,26]. This kind of demand forecasting is essentially a technique that makes use of local sales history and incorporates a search for the foreseeable future [27]. Forecasting, in its most basic form, refers to making predictions which can be carried out with or without the assistance of historical information [28]. This study has incorporated the following methodology, as shown in Figure 1. The paper begins with a comprehensive literature review on forecasting using the ARIMA model, followed by data collection from Company 'X'. The data considered for the study is from the period of April 2010–October 2021, and an ARIMA model is formulated to predict milk production for the upcoming months. The initial model is developed using data from April 2010 to March 2021 to predict milk production from April 2021 to October 2021. The stationarity of the gathered data is assessed to apply the ARIMA model, which is an extension of the autoregressive (AR) and moving average (MA) models.

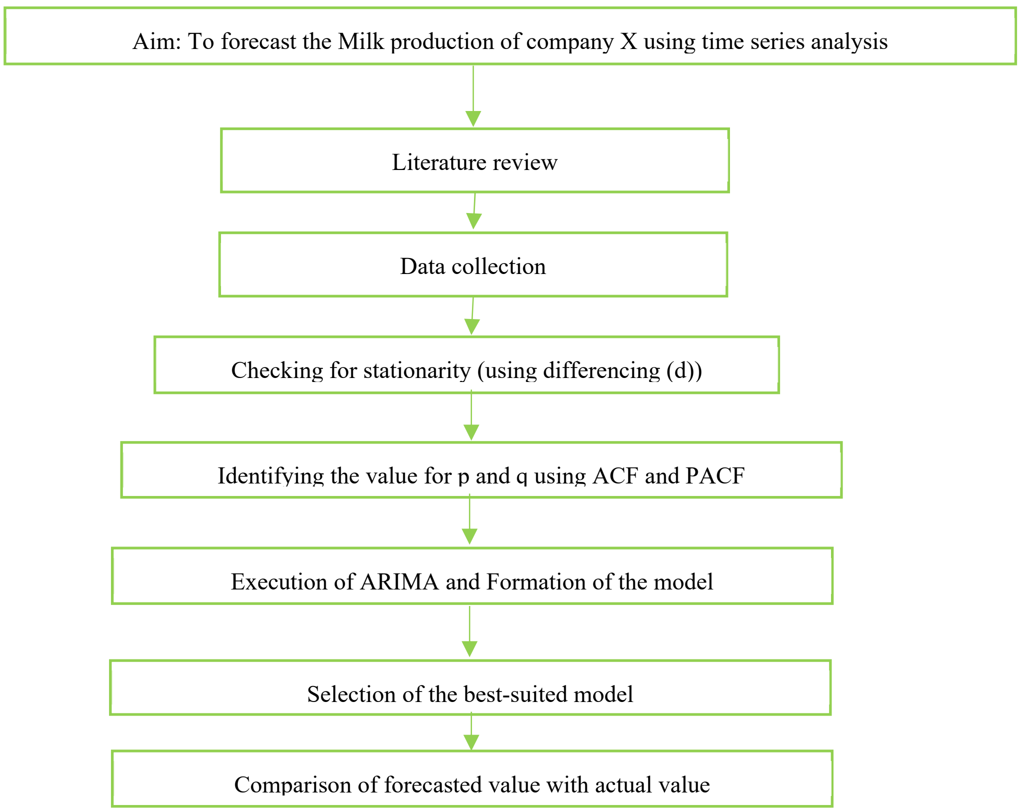

Figure 1. Workflow diagram.

As per the ARIMA model, the analyzed time-series data can be described as a linear combination of their previous values and unpredictable disturbances [29–31]. This model is characterized by three key components: p (representing the autoregressive order), d (indicating the order of differencing required to achieve stationarity), and q (denoting the moving average order). Table 1 demonstrates the model's mathematical form [32,33].

Table 1. AR, MA, and ARMA equations.

Model	Equations	Explanation	Meaning of Terms
AR (p)	$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon$	In the AR model, the current value Y_t is a linear combination of its past values up to order p.	Y_t—current value of the time-series; c—constant; ϕ_1, ϕ_2, . . ., ϕ_p—autoregressive coefficients; ε—white noise error terms.
MA (q)	$Y_t = c - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} + \varepsilon$	In the MA model, the current value Y_t depends on a linear combination of past white noise error terms up to order q.	Y_t—current value of the time-series; c—constant; θ_1, θ_2, . . ., θ_q—moving average coefficients; ε_{t-1}, ε_{t-2}, . . ., ε_{t-q}—white noise error terms.
ARMA	$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \varepsilon - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q}$	The ARMA model combines both AR and MA components, expressing the current value Y_t as a combination of past values and past error terms.	Y_t—current value of the time-series; c—constant; ϕ_1, ϕ_2, . . ., ϕ_p—autoregressive coefficients; ε—white noise error term; θ_1, θ_2, . . ., θ_q—moving average coefficients; ε_{t-1}, ε_{t-2}, . . ., ε_{t-q}—white noise error terms.

As the estimate approach is only applicable to stationary series, ensuring that the series under consideration is stationary is the first and most crucial criterion for ARIMA modelling [34,35]. If neither a series' mean nor its autocorrelation change over time, it is said to be stationary [36,37]. Using a time plot tests, one must determine whether a time-series is stationary. A non-stationary series may be turned into or recognized as a stationary series through distinguishing. The number of differentiations required to obtain stationarity is indicated by the symbol d, which stands for the order of integration/difference. To predict milk production, the ARIMA model is used once the p, d, and q values are obtained. The statistical program SPSS is utilized in this paper's ARIMA modelling. Data transformation, regression analysis, variance analysis, multivariate analysis of variance, analysis of covariance, *t*-tests, non-parametric tests, time-series forecasting, and many more statistical applications may all be performed using SPSS [38–40].

3. Model Formation

The ARIMA model involves multiple processes to arrive at a final forecasting value [41]. A variety of tools are used in the forecasting process, including ACF and PACF [42], both of which play an important role. The data obtained from Company 'X' is plotted in Figure 2, revealing an increasing trend in the data followed by some decreasing trend. To prepare the data for ARIMA analysis, a process called differencing is employed. Differencing involves subtracting a previous observation from the current one to stabilize the data and make it suitable for ARIMA modeling. In the case at hand, this differencing process is depicted in Figures 3 and 4.

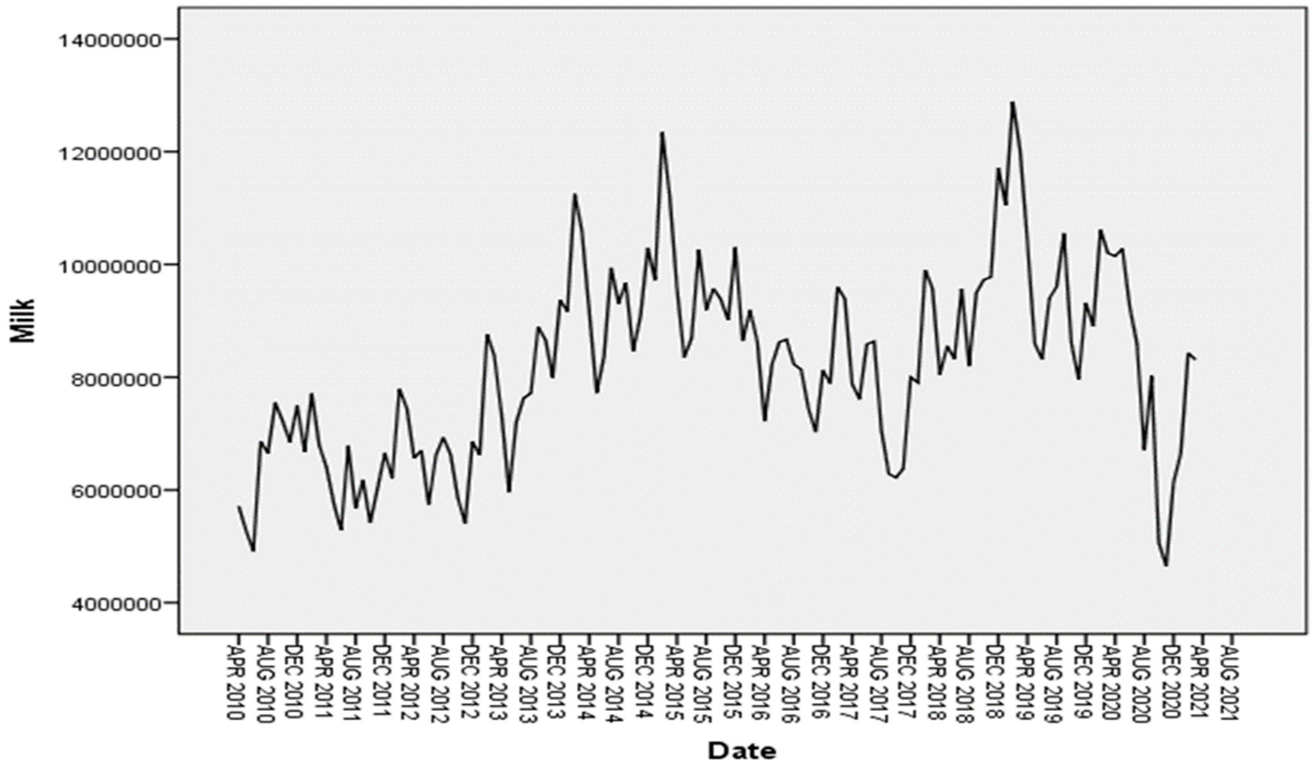

Figure 2. Monthly milk production (in Kgs).

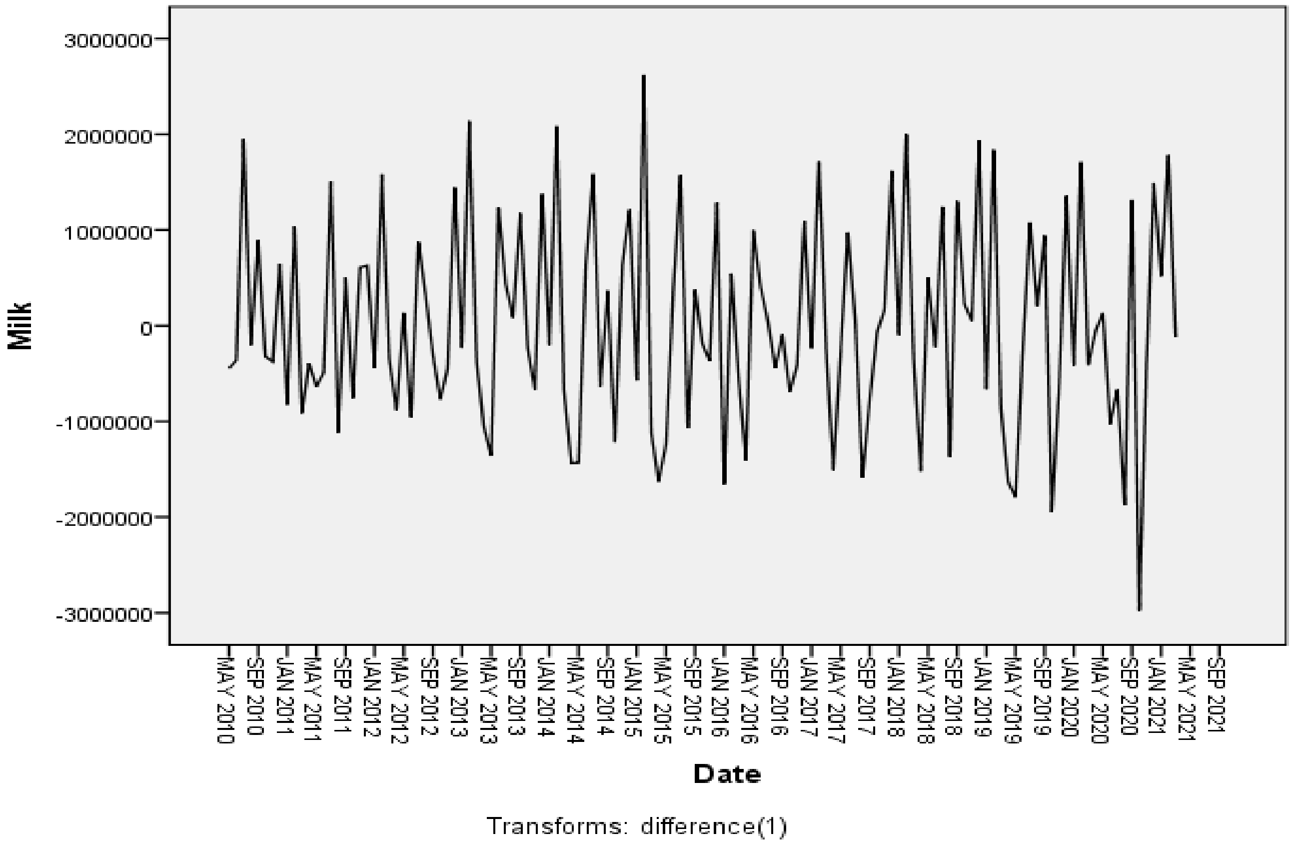

Figure 3. Monthly production data, with d = 1 (in Kgs).

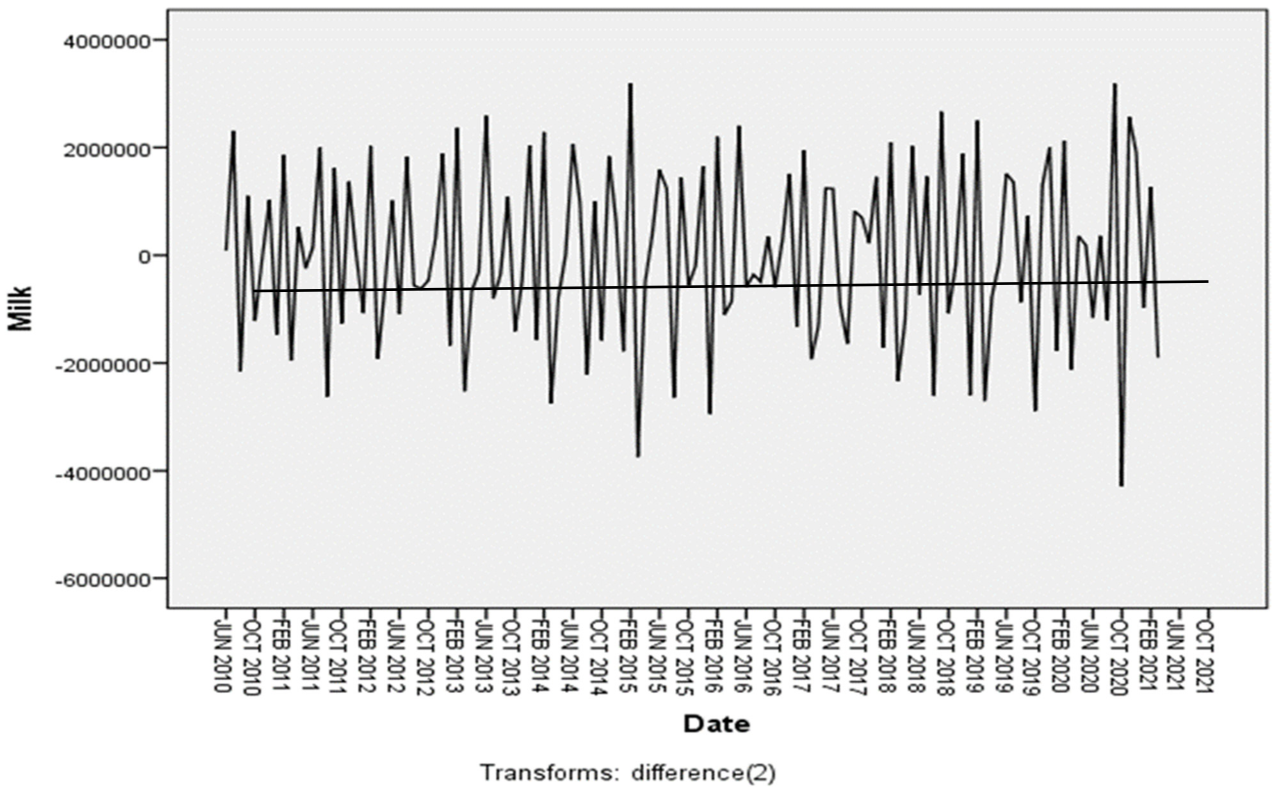

Figure 4. Monthly production data, with d = 2 (in Kgs).

As illustrated in Figure 3, an initial differencing of d = 1 is applied to the data. This transformation is employed to remove any linear trends or periodic fluctuations in the data. However, upon closer examination of the results in Figure 3, it becomes apparent that the data still exhibit deviations from a consistent mean value. This indicates the presence of further non-stationarity, prompting the need for an additional differencing step. In Figure 4, a second differencing operation, denoted by d = 2, is executed. This second differencing process serves to further stabilize the data by eliminating any residual fluctuations and ensuring that the data adhere to a constant mean. The result, as depicted in Figure 4, showcases data that appear more stationary, making them better suited for ARIMA modeling. Consequently, ACF and PACF are used to determine the value of p and q [43]. If the ACF is geometric and the PACF is significant to lag p, then the MA component will be zero, i.e., p = 0, as shown in Table 2. Similarly, if the PACF is geometric and ACF is significant to lag q, then the AR component will be zero, i.e., q = 0. However, if both components are significant, then both p and q are considered. In this study, the SPSS software is used for the formation of ACF and PACF, followed by the final formation of the model. Initially, the data are input into the software, followed by integrating the difference (d = 2) to deploy ARIMA. The p and q values are identified with the help of ACF and PACF provided by SPSS. The ACF and PACF provided by SPSS are shown in Figures 5 and 6, respectively. The formulation of the model is completely dependent on the values of p, d, and q. As shown in Figure 4, d = 2 provides stationarity to the data. Moreover, the value of p and q is determined with the help of Figures 5 and 6.

Table 2. Model selection using ACF and PACF.

	ACF	**PACF**	**Model**
AR (p)	Geometric	Significant until p lags	(p, d, 0)
MA (q)	Significant until q lags	Geometric	(0, d, q)
AR (p) MA (q)	Significant until q lags	Significant until p lags	(p, d, q)

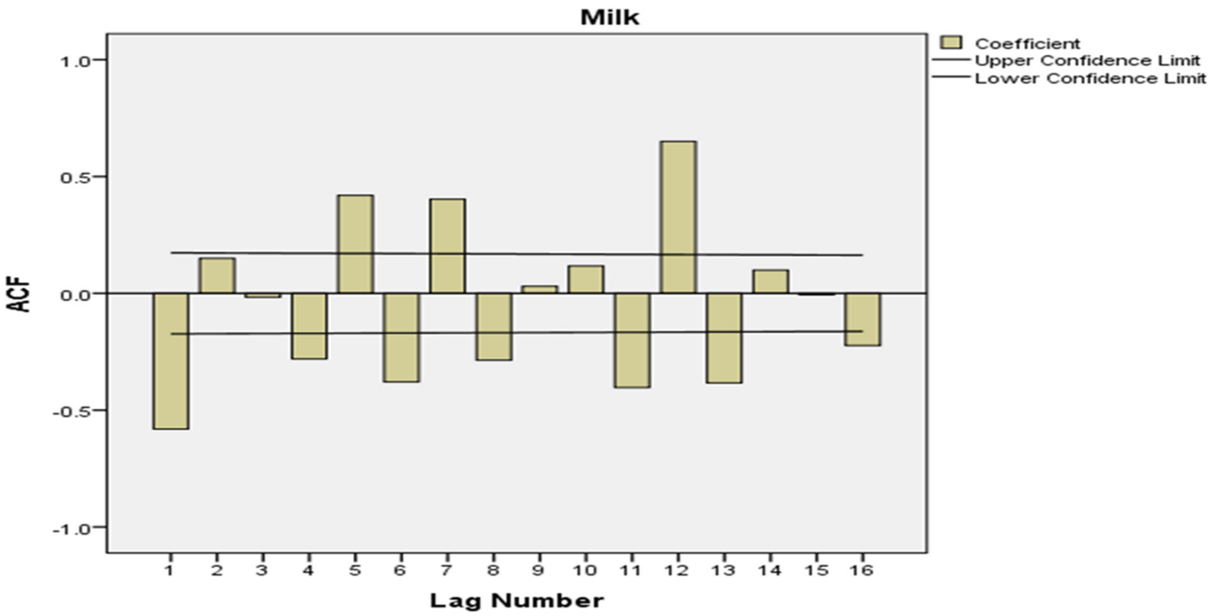

Figure 5. ACF.

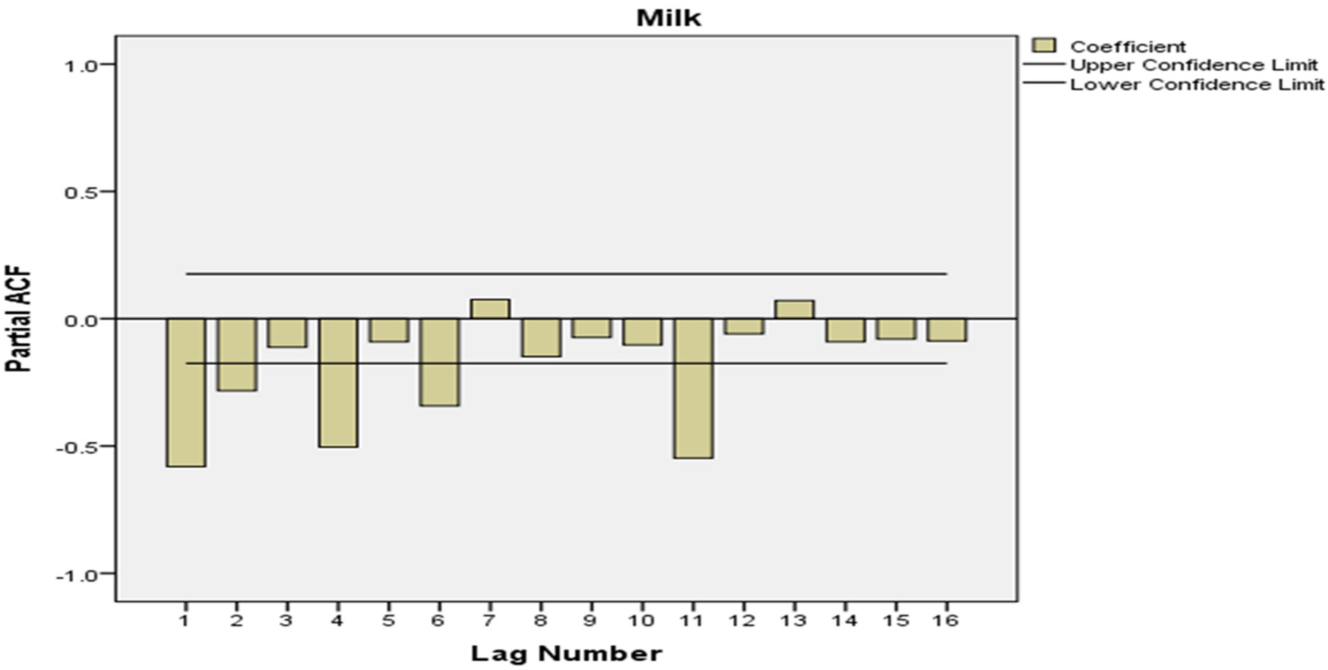

Figure 6. PACF.

After examining the ACF and PACF, it was found that both were significant to lag q (1, 2) and lag p (1, 2), indicating that both the AR and MA components needed to be included in the model [44]. The optimal model for forecasting milk production in North India using the ARIMA model was determined through generating and comparing all the potential models that are described in Table 3.

Table 3. Possible models using ACF and PACF.

AR (p)	I (d)	MA (q)	ARIMA (p, d, q)
1	2	1	ARIMA (1, 2, 1)
2	2	1	ARIMA (2, 2, 1)
2	2	2	ARIMA (2, 2, 2)
1	2	2	ARIMA (1, 2, 2)

4. Result and Discussion, Implications, and Limitations

4.1. Results and Discussion

The first stage in time-series analysis involves visually evaluating the behaviors of the data by plotting them. This visual representation provides a valuable insight into the underlying patterns and trends that exist in the data. Figure 2 depicts the monthly production of milk production of Company 'X' from April 2010 to October 2021 as a function of time. This graph shows an initial upward trend followed by a sudden downward trend. The second differentiation of the data is used to set the stationarity of the data. However, Figure 4 displays the time plots of the differenced series, revealing that the second-order differenced series is stagnant. Once the data have achieved stationarity, the next step is to use ACF and PACF to identify the value of p and q. In Figures 5 and 6, it can be easily noticed that both ACF and PACF are significant to some lags. ACF is significant to lag 1 and lag 2, which decides the value of q = 1 and 2. PACF is also significant to lag 1 and lag 2, which decides the value of p = 1 and 2. Different values in p and q lead to the formation of different (p, d, q) values causing the formation of various ARIMA models. Once the models were identified, it was incorporated into the SPSS software, which generated forecasts for all conceivable models [40]. The software generated forecasts for ARIMA (1, 2, 1), ARIMA (2, 2, 1), ARIMA (2, 2, 2), and ARIMA (1, 2, 2), as illustrated in Figures 7–10, respectively.

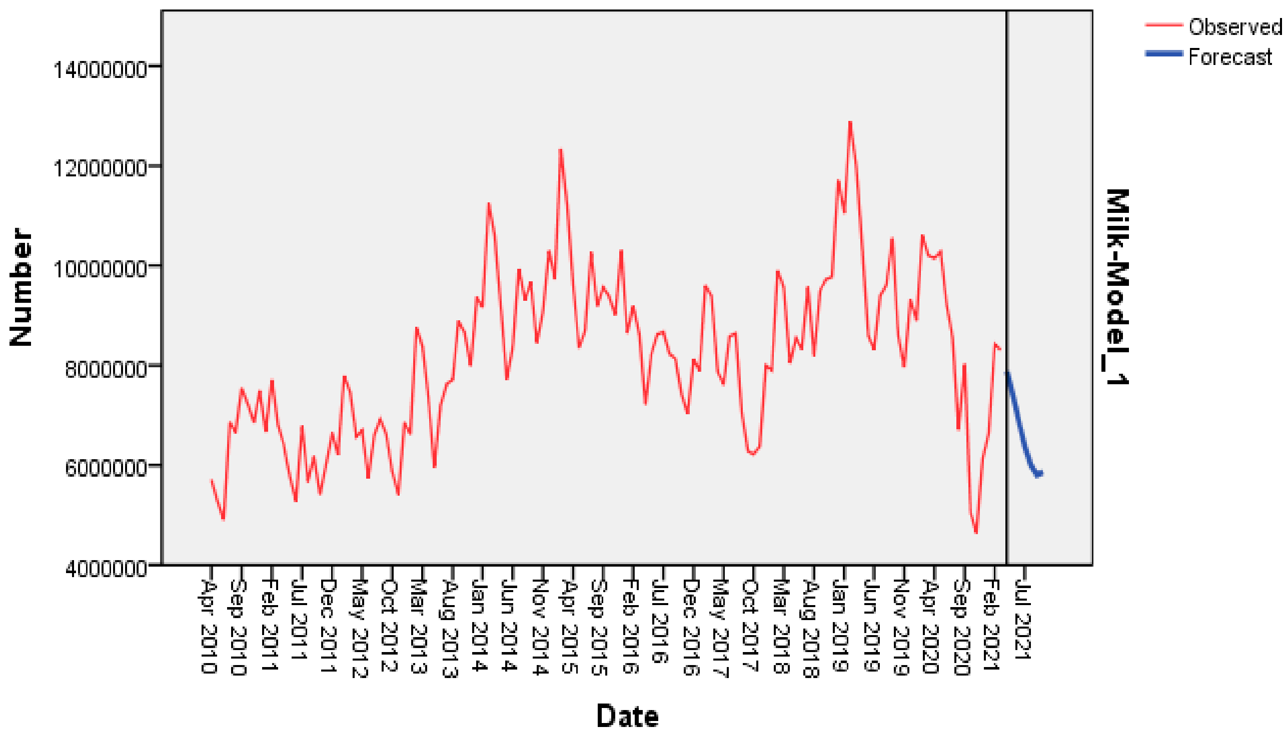

Figure 7. ARIMA (1, 2, 1). *y*-axis—milk production (Kgs); *x*-axis—month.

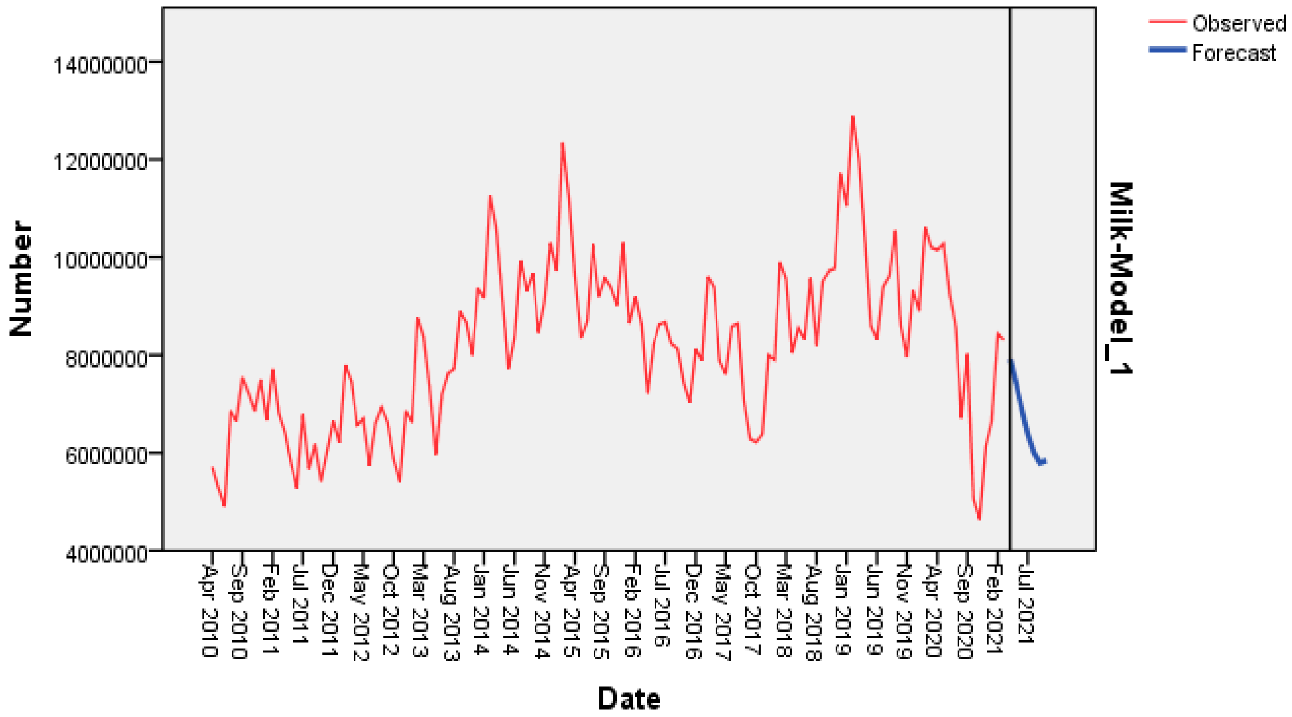

Figure 8. ARIMA (2, 2, 1). *y*-axis—milk production (Kgs); *x*-axis—month.

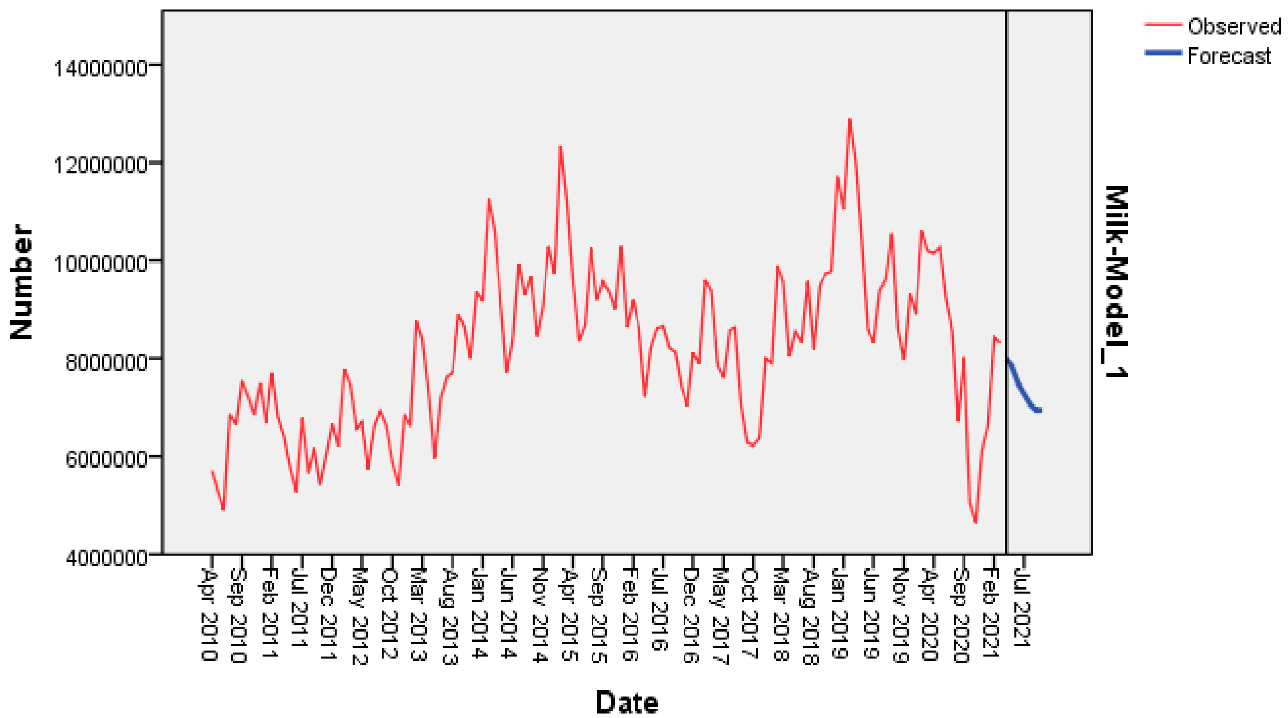

Figure 9. ARIMA (2, 2, 2). *y*-axis—milk production (Kgs); *x*-axis—month.

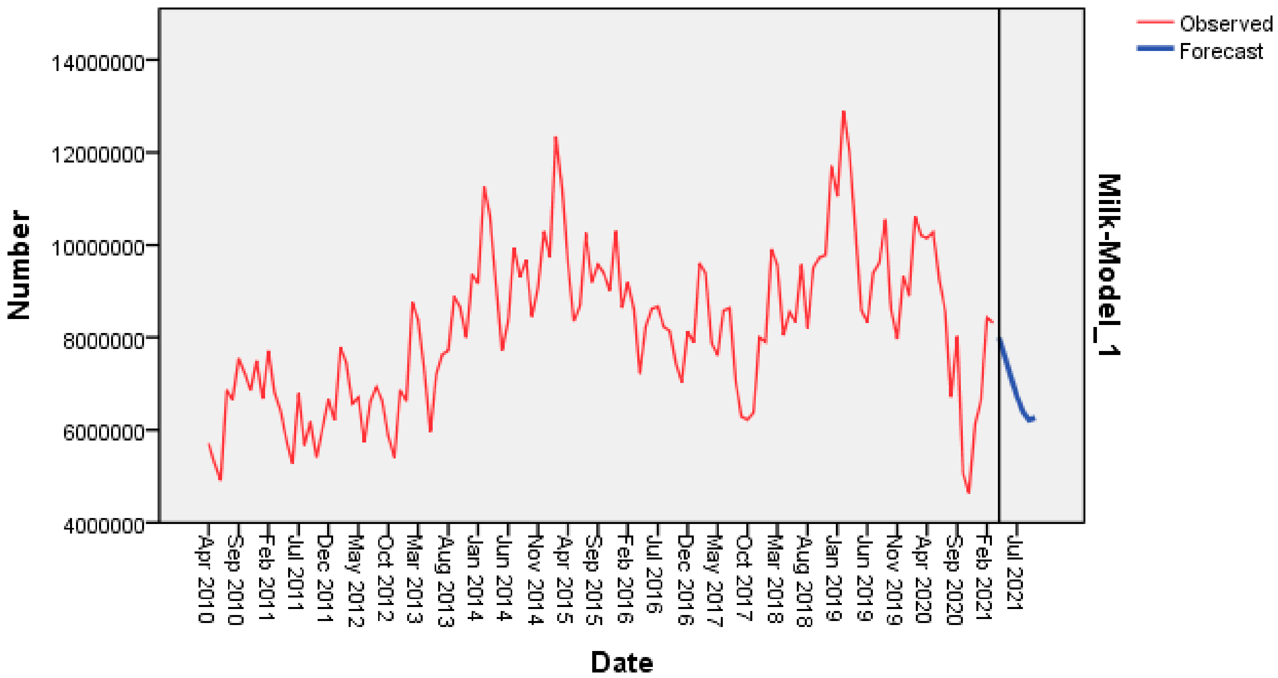

Figure 10. ARIMA (1, 2, 2). *y*-axis—milk production (Kgs); *x*-axis—month.

The forecasted value from April 2021 to October 2021 for each of the models is listed in Table 4. Moreover, the actual value of the milk production from April 2021 to October 2021 is compared with the forecasted value and represented in Figure 11.

Table 4. Forecasting results.

Month	Actual Production (Kgs)	ARIMA (1, 2, 1)	ARIMA (2, 2, 1)	ARIMA (2, 2, 2)	ARIMA (1, 2, 2)
April 2021	7,276,530	7,915,560	7,883,079	7,990,791	7,995,746
May 2021	7,284,150	7,420,933	7,401,705	7,844,204	7,577,291
June 2021	7,428,660	6,885,345	6,874,768	7,500,731	7,134,018
July 2021	6,240,510	6,385,984	6,383,390	7,278,260	6,714,827
August 2021	4,304,730	6,385,984	6,002,114	7,057,491	6,390,933
September 2021	4,006,170	5,793,478	5,804,899	6,943,595	6,216,954
October 2021	3,665,070	5,849,720	5,865,956	6,947,270	6,259,852

All four models show a consistent downward trend in milk production. However, it is crucial to note that the accuracy of these models varies across different months. For the initial months, spanning from April 2021 to July 2021, all four models performed relatively well, with their predictions closely aligning with the actual production data generated by Company 'X' (Figure 11). However, this accuracy begins to decline after July 2021. The abrupt shift in forecast accuracy post-July 2021 can be primarily attributed to the significant disruptions caused by the second wave of the COVID-19 pandemic. The sudden change in procurement processes within the cold supply chain (CSC) had a profound impact on milk production and distribution, making it challenging to accurately predict production levels during this period. Besides the COVID-19-related disruptions, several other factors might contribute to the difficulty in accurate predictions. These may include seasonality, changes in consumer preferences, variations in cattle health, or shifts in feed availability [45].

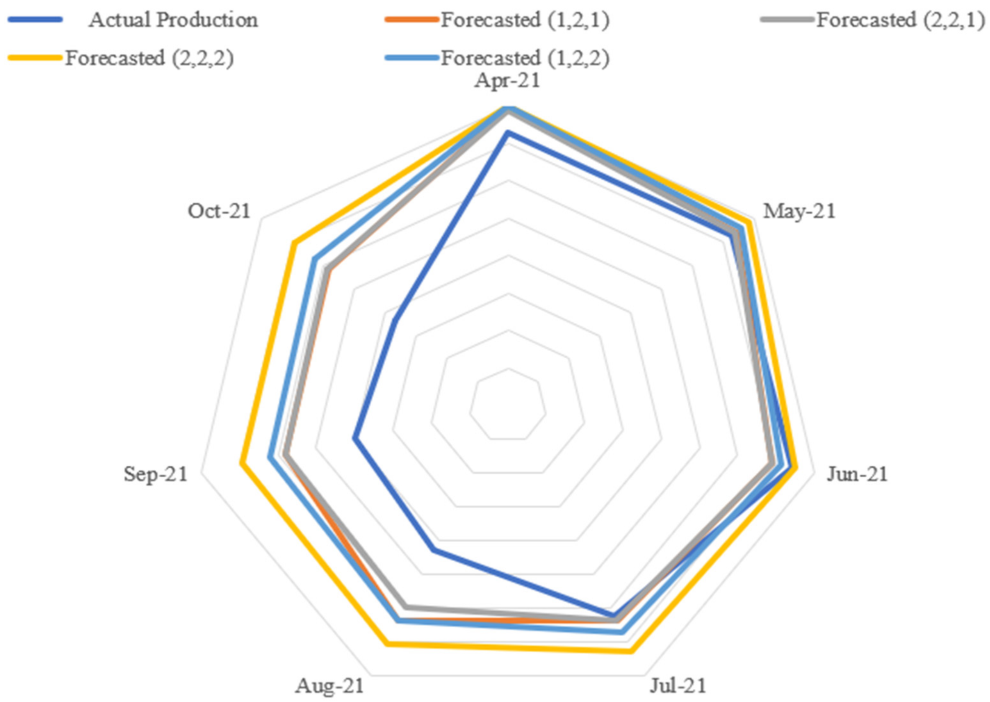

Figure 11. Comparison between the models.

Furthermore, the models are checked for validation using MAPE and R^2. The forecasting model with an optimized value between MAPE and R^2 was chosen as the best model to predict milk production in North India using the ARIMA model [46]. Table 5 represents the results of four different ARIMA models, each evaluated using two performance measures: the MAPE and the R^2 value. The ARIMA models are differentiated by their order, which specifies the number of autoregressive, integrated, and moving average terms used in the model. For example, ARIMA (1, 2, 1), which has one autoregressive term, two differences, and one moving average term. However, the MAPE indicates the average percentage deviation of the forecasted values from the actual values for each model [47]. For instance, the ARIMA (2, 2, 1) model has a MAPE of 21.3%, indicating that, on average, the predicted values exhibit a difference of around 21.3% compared to the actual milk production values. The R^2 shows the proportion of the variance in the actual values that is explained by the forecasted values. As an illustration, the ARIMA (2, 2, 2) model achieved an R^2 value of 0.818, indicating that approximately 81.8% of the variation in the actual values can be accounted for by the forecasted values [48]. While the ARIMA (2, 2, 2) model may have a higher R^2 value, indicating a better explanatory power, it also has a higher MAPE value, suggesting a higher average percentage deviation between the forecasted and actual values. This higher MAPE value indicates that, on average, the ARIMA (2, 2, 2) model's forecasts deviate more from the actual values compared to the ARIMA (2, 2, 1) model. In forecasting scenarios, it is crucial to strike a balance between accuracy and practicality. Although the ARIMA (2, 2, 1) model has a marginally lower R^2 value, it exhibits a lower MAPE value, signifying superior overall accuracy in predicting milk production values [49]. This model's forecasts exhibit a smaller average percentage deviation from the actual values compared to the ARIMA (2, 2, 2) model. Therefore, considering both the R^2 value and MAPE, the decision to choose the ARIMA (2, 2, 1) model as the best-performing model is based on its ability to provide more accurate and sustainable forecasts, which is ultimately more valuable in practical applications.

Table 5. Forecasting error.

Model	MAPE	R^2
ARIMA (1, 2, 1)	22.6	0.739
ARIMA (2, 2, 1)	21.3	0.790
ARIMA (2, 2, 2)	37.4	0.818
ARIMA (1, 2, 2)	28.4	0.793

4.2. Implications

The implications of accurate milk production forecasts presented in the study, combined with the assessment of the cold supply chain, are of great significance for the dairy industry, with far-reaching effects on sustainability and the achievement of the SDGs [21]. The dairy sector plays a critical role in supporting food security, responsible consumption and production, economic growth, and environmental sustainability [50–52]. Moreover, the efficiency and sustainability of the cold supply chain, a vital component of the dairy industry, directly impacts these aspects [53,54]. Forecasting accuracy using ARIMA models can act as a powerful tool in promoting efficiency, resilience, and better decision making within the industry. Considering this comprehensive perspective, the study's findings have significant implications (Figure 12), which are detailed below.

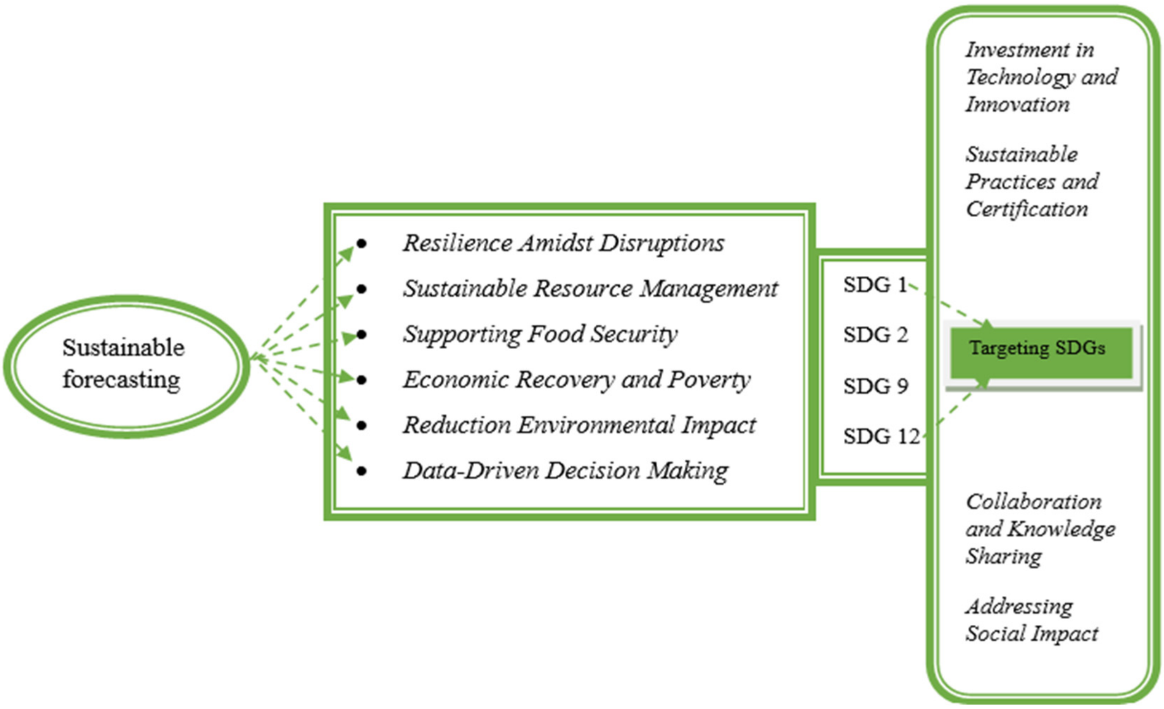

Figure 12. Sustainable forecasting implications and targeted SDGs.

1. Resilience amidst disruptions: The stark deviations observed between the forecasted and actual production values, particularly evident post-July 2021, attest to the dairy industry's vulnerability to unforeseen disruptions like the COVID-19 pandemic. This pronounced impact underscores the paramount importance of accurate milk production forecasts [55,56]. Furthermore, the cold supply chain's role in maintaining product quality and safety during such disruptions cannot be underestimated. By harnessing the insights offered by ARIMA models, stakeholders can proactively navigate challenges, restructure supply chains, and avert supply gaps, bolstering the resilience of the CSC alongside industry-wide resilience [57]. This strategic preparedness is in direct harmony with the essence of SDG 9—"Industry, Innovation, and Infrastructure"—ensuring industry resilience against unexpected upheavals.

2. Sustainable resource management: A closer examination of the disparities revealed in the comparison highlights a significant area of focus for dairy sector resource management. The fluctuations between predicted and actual values underscore the criticality of judiciously managing resources such as water, energy, and feed [58,59]. Effective resource management within the CSC is vital for energy-efficient refrigeration and transportation. By narrowing the variance, dairy producers and the CSC can minimize waste, optimize resource utilization, and actively contribute to the realization of SDG 12—"Responsible Consumption and Production". This alignment fosters a sustainable approach while balancing milk production demands [60].
3. Supporting food security: The juxtaposition of forecasted and actual values accentuates the dairy industry's crucial role in upholding food security, particularly in the face of global disruptions. The disparities between predicted and actual production patterns during challenging periods underscore the potential of precise milk production forecasts to mitigate food shortages and prevent wastage [61–63]. Considering SDG 2—"Zero Hunger"—this alignment becomes a cornerstone in ensuring consistent cold supply chain [64,65], supporting nutrition needs, and stabilizing communities [66].
4. Economic recovery and poverty reduction: The disparities observed, particularly in times of disruption, delineate the dairy industry's significance in promoting economic recovery and reducing poverty [67–69]. The accuracy of forecasts empowers decision makers to navigate uncertain terrain effectively. This strategic clarity, in alignment with SDG 1—"No Poverty"—becomes pivotal in safeguarding livelihoods, bolstering economic stability, and fostering long-term prosperity within the dairy sector.
5. Environmental impact: The discernible variations between forecasted and actual values underscore the industry's journey towards environmental stewardship. These deviations reflect the direct influence of forecasted trends on resource utilization, waste generation, and sustainability practices. By achieving a closer accord between predictions and actual outcomes, the dairy sector contributes to the principles of SDG 12, culminating in more sustainable production patterns [70].
6. Data-driven decision making: The disparities unveiled by the comparison between forecasts and actuals substantiate the dairy industry's progression towards data-driven decision making. These deviations act as a compass, guiding industry stakeholders to better comprehend production dynamics, identify opportunities, and address bottlenecks. This strategic transformation, in consonance with the core tenets of the SDGs, underscores the pivotal role of data-driven policies in steering the sector towards sustainable development [71–73].

The convergence of these implications, borne out of the comparison between forecasted and actual production values, underscores the dairy industry's trajectory towards sustainability and SDG alignment. The responsive strategies, guided by insights from accurate predictions, amplify the industry's commitment to responsible practices and enduring growth in the face of disruptions. However, to improve sustainability and the achievement of the SDGs in the face of such disruptions, the dairy industry needs to adopt a holistic approach, as follows [66]:

- Investment in technology and innovation: Embracing technology and innovation can improve production efficiency and reduce the industry's environmental footprint. For instance, advanced data analytics and IoT technologies can optimize resource utilization and enable real-time decision making.
- Sustainable practices and certification: Encouraging and incentivizing sustainable farming practices can promote responsible production. Certifications such as "organic" or "sustainable" can help consumers make more sustainable choices and contribute to achieving SDG 12.
- Collaboration and knowledge sharing: Collaborating with stakeholders, including governments, NGOs, and research institutions, can foster knowledge sharing and best practices. This collective effort can enhance the industry's sustainability and contributions to the SDGs.

- Addressing social impact: The COVID-19 pandemic's socioeconomic effects highlighted the importance of considering the social impact of dairy production. Ensuring fair wages, safe working conditions, and community engagement can align the industry with SDG 8—"Decent Work and Economic Growth".

4.3. Limitations

One limitation of this analysis presented in the above discussion is its potential inability to accurately predict unexpected or sudden changes in the data. For instance, the second wave of COVID-19 caused a significant disruption in the procurement process, leading to deviations between forecasted and actual values after July 2021. This highlights the challenge of capturing abrupt shifts or anomalies in the data using the ARIMA models, potentially limiting their effectiveness in certain dynamic scenarios. Moreover, it is essential to recognize that the time-series analysis in this study focuses solely on a single variable, which is the milk production data. Though the ARIMA model is valuable in capturing time-related patterns, they may not account for other external factors that could influence milk production sustainability. Factors such as weather conditions, shifts in government policies, and evolving consumer preferences can also impact milk production levels and the dairy industry's ecological footprint.

5. Conclusions and Future Perspective

This study has demonstrated the power of time-series analysis, particularly the ARIMA models, in forecasting and managing monthly milk production within the complex landscape of the CSC. By meticulously examining historical data from April 2010 to March 2021 and making projections up to October 2021, we have gained valuable insights into the dynamics of milk production for Company 'X'. The findings reveal the strengths and limitations of various ARIMA models, with ARIMA (2, 2, 1) standing out for its remarkable accuracy in predicting milk production, boasting a low MAPE value of 21.3. On the other hand, ARIMA (2, 2, 2) demonstrated a superior R^2 value of 0.818, indicating a robust alignment with observed production trends. However, it also exhibited a higher MAPE of 37.4, highlighting the challenges that are encountered in capturing and predicting unforeseen disruptions. Additionally, the study's timing coincided with the COVID-19 pandemic's second wave, which significantly impacted the CSC in the study area. This disruption serves as a stark reminder of the need for robust forecasting that considers external factors, especially within the context of supply chain management. The study underscores the importance of visual analysis, data stationarity, and thoughtful model selection as essential tools in refining predictions for CSCs. These steps are pivotal in ensuring reliability in dairy industry forecasts and facilitating informed decision making, ultimately contributing to the sustainability of the cold supply chain. Furthermore, our research has contributed to the growing body of knowledge in time-series analysis within the dairy sector. It highlights the potential of data-driven approaches, especially pertinent in the context of the CSC, where accurate forecasts are critical not only for supply but also for effective storage and distribution. Beyond its technical contributions, this study emphasizes the broader implications for sustainability and alignment with the SDGs within CSCs. The dairy industry's commitment to incorporating sustainability principles, making data-driven decisions, and addressing the impacts of disruptions positions it as a crucial player in resilience-building activities and environmental stewardship. In a post-pandemic context, the dairy sector within the studied CSC is well-positioned to lead the way in sustainable development, optimizing the demand–supply dynamics of this essential commodity while contributing positively to society and the global community. As we move forward, further exploration of advanced forecasting models and continued adaptation to changing dynamics will be essential in ensuring the long-term success of the dairy industry within CSCs.

In terms of future perspectives, the present study suggests exploring seasonal ARIMA (SARIMA) models and machine learning algorithms, specifically within the cold supply chain. SARIMA models are adept at handling seasonal variations in milk production;

this is crucial for managing dairy products that require temperature control. Machine learning, especially neural networks, can be harnessed to decipher intricate relationships within CSCs. This entails optimizing the storage, transportation, and distribution of dairy products under controlled temperatures. These advanced techniques promise more precise and sustainable predictions, enhancing efficiency and minimizing waste. By integrating these technologies into the cold supply chain, the dairy industry can become aligned with sustainability objectives, enabling it to contribute more effectively to the SDGs.

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