Project Report On

FROM LOOM TO MARKET : ANALYZING HANDLOOM CLOTH PRODUCTION & SALES IN CHENDAMANGALAM

Submitted in partial fulfilment of the requirements for the degree of

MASTER OF SCIENCE

in

APPLIED STATISTICS AND DATA ANALYTICS

by

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CERTIFICATE

This is to certify that the dissertation entitled, **FROM LOOM TO MARKET : ANALYZING HANDLOOM CLOTH PRODUCTION & SALES IN CHENDAMANGALAM** is a bonafide record of the work done by Ms. **FATHIMA JANNATH** under my guidance as partial fulfilment of the award of the degree of **Master of Science in Applied Statistics and Data Analytics** at St. Teresa's College (Autonomous), Ernakulam affiliated to Mahatma Gandhi University, Kottayam. No part of this work has been submitted for any other degree elsewhere.

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DECLARATION

I hereby declare that the work presented in this project is based on the original work done by me under the guidance of Smt. **ARUNIMA P S** , Assistant Professor, Department of Mathematics, St. Teresa's College(Autonomous), Ernakulam and has not been included in any other project submitted previously for the award of any degree.

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Date:12/03/2025 SM23AS003

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ABSTRACT

The handloom industry is a vital component of India's textile heritage, with both cultural and economic significance. Chendamangalam, a renowned handloom hub in Kerala, has a long tradition of producing intricately woven fabrics that reflect the region's rich craftsmanship. However, the industry faces numerous challenges, including fluctuating consumer demand, market competition, and economic pressures that hinder its growth and sustainability. This study aims to analyze the trends in Chendamangalam's handloom textile production and sales, leveraging historical data from 1973 to 2023.

To achieve this, advanced statistical and forecasting techniques are applied. The Compound Annual Growth Rate (CAGR) is analyzed to assess long-term industry growth. Linear Regression is employed to identify production and sales trends and determine the most effective forecasting model. Additionally, the ARIMA model is utilized to project future production and sales performance for the period 2024–2034. By evaluating and comparing these forecasting models, the research aims to provide valuable insights into the industry's trajectory.

The findings of this study will assist policymakers, stakeholders, and handloom manufacturers in making informed decisions that support the sustainable development and expansion of the Chendamangalam handloom industry.

Keywords: *Handloom industry, Production forecasting, Sales trends, Economic sustainability, Market analysis, Growth patterns, Statistical modeling, Linear Regression, ARIMA model, Compound Annual Growth Rate (CAGR), Forecasting techniques, Chendamangalam handloom sector.*

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CHAPTER 1
INTRODUCTION

An essential part of India's rich textile legacy, the handloom sector is valuable both culturally and commercially. Chendamangalam in the state of Kerala is notable among the many areas known for their handloom workmanship because of its long history of creating beautifully woven fabrics that frequently showcase the region's cultural variety and skilled craftsmanship. Despite its significance, Chendamangalam's handloom industry has difficulties that limit its sustainability and expansion, including shifting consumer demand, fierce competition in the market, and economic pressures.

In order to comprehend the underlying trends, predict future production and sales, and spot growth patterns, this project intends to conduct a thorough analysis of Chendamangalam's handloom textile production and sales. The use of sophisticated statistical and forecasting tools is specifically highlighted in order to assess the industry's present state and forecast performancefor2024to2034. The ultimate goal of this research is to give stakeholders, legislators, and handloom manufacturers a better grasp of the dynamics of the Chendamangalam handloom market so they may make wise decisions for the sector's expansion and sustainable development.

India’s handloom industry, vital for rural employment and exports, faces challenges from power looms, low wages, and poor working conditions. Chendamangalam, known for its kasavu sarees, struggles with declining weaver participation and setbacks like the 2018 floods. Despite government aid, uncoordinated efforts hinder revival. This proposal suggests improving weavers’ livelihoods through better infrastructure, fair trade, and market expansion via tourism and branding. By modernizing while preserving tradition, it aims to create jobs, prevent migration, and ensure a sustainable future for the handloom sector. Rajeev (2021)

Chekutty dolls emerged as a symbol of resilience after the 2018 Kerala floods, upcycled from damaged Chendamangalam handloom fabric to support weavers. Social entrepreneurs Lakshmi Menon and Gopinath Parayil initiated the project, ensuring the fabric was disinfected and repurposed. Despite global demand tied to the "Rebuilding Kerala" movement, Chekutty struggled to capture local markets in Kerala. A study with 260 respondents, including loyal customers and weaving society members, explored promotional challenges. Using judgmental sampling, the study proposed strategies to enhance Chekutty's market visibility and local appeal. Harish (2019).

The handloom industry serves as a vital source of livelihood for both rural and urban populations across India. This study primarily focused on 13 key handloom-producing states, each contributing over one percent to the total employment in the sector, collectively accounting for 93 percent of the workforce. The findings highlighted employment growth in the handloom weaving industry and examined the status of workers. Data from the Handloom Census reports of 2009–10 and 2019–20 formed the basis of the analysis. The study revealed that while employment in the sector declined at the national level, four states experienced a positive CAGR in the number of workers between 2009 and 2019. Additionally, it explored various aspects such as work nature, patterns of engagement, average working days, household income, and interstate differences. Baruah et al, (2022)

1.1 About the data

For the purpose of study, the data was collected from Handloom Weaver's Co-operative Socity Ltd. no. H47 Chendamangalam. The data set consist of yearly data value of production and sales of handloom clothes over 5 decades (1973-2023).

1.2 Objectives of the Study

- To analyze the COMPOUND ANNUAL GROWTH RATE (CAGR) of handloom cloth production in Chendamangalam over a specific period.
- To identify trends in handloom cloth production and sales over the past 50 years and compare the trend to find which one is better for forcasting using LINEAR REGRESSION.
- To model and forecast future value based on past production and sales data using ARIMA model

CHAPTER 2
REVIEW OF LITERATURE

Padhan, (2012) given many variables influencing agricultural output in India, including rainfall, the usage of fertilizer and pesticides, the climate, and subsidies, forecasting this sector is essential. Using data from 1950 to 2010, the ARIMA model was used to predict the yearly productivity of 34 distinct agricultural products. Criteria including the lowest MAPE values, minimum AIC, and Adj R2 were used to confirm the validity of the model. Cardamom had the lowest AIC value and tea the lowest MAPE value. When it came to sugarcane, papaya had the greatest MAPE and AIC rating. However, given the variety of factors influencing agricultural output, the model's dependability can be called into doubt. Therefore, additional information for agricultural product forecasting could be incorporated into a rethinking of other forecasting models.

Sankarakumar (2016), explores the manufacturing of handloom fabrics in India over the past 35 years, focusing on data from 1980-1981 to 2014-2015. The study aims to understand the impact of economic reform on textile production before and after the 1990s economic changes. Secondary data was sourced from the Indian Khadi and Village Industries Commission, Ministry of Textile, and the Textile Commissioner. Statistical methods were used to analyze the data.

Fattah et al, (2018) This article presents a time series approach for modeling and forecasting food demand in a company. It uses historical demand data to develop autoregressive integrated moving average (ARIMA) models, which are validated using historical demand information. The model, which corresponds to ARIMA (1, 0, 1), is suitable for food manufacturing and can provide reliable guidelines for managers in making decisions. The study demonstrates the potential of historical demand data in predicting future demand and its impact on supply chains.

Harish (2019) follows the destruction of Chendamangalam weaving units by floods, chekutty—a distinctive manifestation of a community's culture—was brought back to life. Lakshmi Menon and Gopinath Parayil, social entrepreneurs, made dolls out of ruined cloth to represent sacrifice and rebirth. Chekutty, however, had trouble breaking into local markets, especially in Kerala. A study was carried out to determine the difficulties Chekutty encountered with its marketing plans and to offer recommendations for raising the company's profile in the marketplace. 260 devoted clients and HWCS members from Chendamangalam provided the data.

Rajeev, (2021) conveys that due to inefficient government programs, unfair competition, and a lack of exposure to emerging technology, the handloom industry—a traditional occupation—faces competition from domestic textile mills and a crisis of livelihood. The division of activity and lack of stakeholders further impede the craft's resurgence. In order to create immunity and advance institutions globally, a proposal should include working conditions, market/demand scenarios, marketing methods, and future research scopes. With tourism playing a significant part in growing the consumer base, the program seeks to expand the handloom industry. This will create jobs and dignity by bridging the divide between the rural and urban sectors.

Darji, (2021) this study examines the development of Haryana's textile sector during a ten-year period, from 2008–09 to 2017–18. The study uses quantitative analysis and secondary data, taking into account variables such as cotton output, area, and exports of raw cotton, handloom, and handicrafts. Correlation, regression, CAGR, and trend analysis have all been used to help the data analysis. Area and production were shown to be positively correlated (0.68). During the ten-year study period, cotton production and productivity increased at a compound annual growth rate (CAGR) of 7%, with the exception of 2015–16, when they fell by 37% as a result of the leaf curl virus and whitefly pest onslaught in Haryana. Raw cotton, handloom, and handicraft export data all exhibit a positive linear trend.

Baruah et al, (2022) proposes the handloom industry in India offers livelihood opportunities to both rural and urban populations. A study focusing on 13 major handloom-practicing states revealed growth in employment and worker status. The study used handloom census reports from 2009-10 and 2019-20. Four states showed a positive CAGR in worker numbers from 2009 to 2019, while national levels declined. The research also examined work nature, engagement patterns, working days, and average household income, identifying differences among states. The study highlights the importance of the handloom sector in India's economy.

CHAPTER 3
MATERIALS AND METHODS

3.1 TIME SERIES

A time series is a sequence of data points recorded at successive, uniformly spaced time intervals. Each data point represents a measurement or observation at a particular point in time. Time series data is essential for analyzing how a particular phenomenon evolves over time, allowing us to make forecasts and uncover underlying patterns that would be hard to detect without examining the data over time. Time series data is often used in fields like economics, finance, healthcare, meteorology, and engineering.

Key components

- **Secular Trend**

  The trend represents the long-term movement or direction in the data, showing whether the data is generally increasing, decreasing, or remaining constant over an extended period.

- **Seasonal component**

  Seasonality refers to regular and predictable fluctuations that occur at fixed intervals, such as monthly, quarterly, or yearly, often due to external factors like weather, holidays, or fiscal cycles.

- **Cyclic component**

  Cyclic patterns involve fluctuations that occur over irregular periods, often tied to broader economic or business cycles, and can span multiple years. These cycles can be harder to predict and are typically linked to larger economic or market conditions.

- **Irregular component**

  the irregular component (noise) refers to random variations that do not follow any identifiable pattern or trend. This noise is usually caused by unpredictable or exceptional events and is often considered "background" variability in the data.

3.1.1 ARIMA MODEL

The common statistical technique for time series forecasting is the ARIMA model (AutoRegressive Integrated Moving Average). By studying the historical patterns and correlations between the data, it is frequently used to analyze and forecast future points in a time series.

Assumptions of the ARIMA model

1. **Stationarity :** The data must be stationary, or it should be made stationary through differencing. Stationarity means that the statistical properties of the time series (like the mean, variance, and autocorrelation) do not change over time. If the series is non-stationary, ARIMA requires transformation to make it stationary.
2. **No Seasonality :** Seasonality refers to regular, periodic fluctuations in a time series (e.g., monthly, quarterly, or yearly cycles). If the series has seasonality, a standard ARIMA model might not capture it properly.

Forecasting agricultural productivity in India is complex and essential due to the influence of factors such as rainfall, fertilizer application, climatic conditions, and government subsidies. The ARIMA model was used to predict the annual productivity of 34 crops in India, using data from 1950 to 2010. The model's validity was assessed using criteria like Adjusted R^2, minimum AIC, and the lowest MAPE values. Tea had the lowest MAPE, while cardamom had the lowest AIC. Papaya had the highest MAPE, and sugarcane had the highest AIC value. However, the accuracy of forecasted values depends on the assumption of ceteris paribus, which does not always align favorably with other factors. This highlights the need for alternative forecasting models that incorporate a broader range of influencing variables for more accurate predictions. Padhan, (2012)

The article discusses a study on modeling and forecasting demand in a food company using a time series approach. It demonstrates how historical demand data can be used to predict future demand and assess its impact on the supply chain. The study developed multiple autoregressive integrated moving average (ARIMA) models using the Box-Jenkins time series methodology, with model selection based on Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), maximum likelihood, and standard error. The most suitable model was identified as ARIMA (1,0,1), which was validated using additional historical demand data. The results confirmed that this model is effective for demand modeling and forecasting in food manufacturing, providing managers with reliable insights for decision-making. The article suggests future research should explore alternative forecasting models, including integrating qualitative and quantitative techniques, comparing neural network approaches, and developing a hybrid ARIMA–Radial Basis Function (RBF) model to improve prediction accuracy. Darji, (2021)

Steps to be followed in ARIMA

Step 1: Visualize and Preprocess the Data - To visually check for any trends, seasonality, or abnormalities, plot the time series. If there are any missing values, deal with them by either adding them or eliminating the data points.

Step 2: Check for Stationarity - Use statistical tests like the Augmented Dickey-Fuller (ADF) test to check if the time series is stationary. A stationary series has constant mean, variance, and autocorrelation over time. If the series is non-stationary, apply differencing until it becomes stationary.

Step 3: Identify AR and MA Components (p and q) - Plot ACF and PACF to assess the correlation between the current value and past values while excluding the intermediate lags. The ACF plot helps identify the MA (q) parameter, based on the point where the ACF cuts off. The PACF plot helps determine the AR (p) parameter, based on the point where the PACF cuts off.

Step 4: Fit the ARIMA Model - Use the identified values of p, d, and q to fit the ARIMA model to the data. his step will estimate the coefficients (parameters) for the AR and MA components. Best (p, d, q) can be also determined from Information criteria, such as Akaike Information Criterion (AIC). If the best model parameters are finalized divide the dataset completely into training and testing set. Typically the large set of points should be taken for training. Fit the model to the above chosen ARIMA model parameters for training data.

Step 5: Model Diagnostics - Next step is to diagnostic check of residuals, homoscedasticity, normality. Once the model is fitted, inspect the residuals, The residuals should resemble white noise (no patterns). By performing a Ljung-Box test to verify that they are uncorrelated. Checking homoscedasticity by verify that the residuals don't show any patterns, such as fluctuating variation over time, and that their variance is constant. Shapiro-Wilk test is used to determine if the residuals are normaly distributed.

Step 6: Forcasting - Use the model to predict future values based on the fitted ARIMA model.

Step 7: Model Evaluation - Evaluate the model's performance by comparing the predictions to actual values.

3.2 REGRESSION

Regression is a statistical technique used to understand the relationship between a dependent variable and one or more independent variables. In order to provide information on how the independent variables affect the dependent variable, it attempts to model and examine the relationship between these variables. As regression helps quantify and predict future events based on past data, it is frequently used in data analysis, machine learning, and forecasting.

3.2.1 Linear Regression Model

The most basic and popular type of regression is called linear regression. The dependent variable (Y) and one or more independent variables (X) are assumed to have a linear relationship. The relationship can be expressed as:

$$Y = \beta_0 + \beta_1 X + \in$$

Here β_0 is the intercept,

β_1 is the coefficient (slope), and

ϵ represents the error term

Steps in linear regression model

Step 1: Collect past data containing the independent variables and the dependent variable Address missing values, eliminate duplicates, and fix dataset problems to clean up the data.

Step 2: To visually examine how the dependent and independent variables relate to one another, plot the data. The independent variables that have the strongest relationship with the dependent variable are determined by looking at the correlation between them. This can help in selecting which predictors to add to the model. Outliers can have a significant impact on the linear regression model's results, so identify and manage them.

Step 3: Create a training set and a test set out of the dataset. The model is trained on the training set, and its performance is assessed on the test set. Although this can vary, a typical split is 80% for training and 20% for testing.

Step 4: Use the Ordinary Least Squares (OLS) method to fit a linear regression model. The general equation is:

$$Y = \beta_0 + \beta_1 X + \in$$

where:

- Y= Dependent variable (target, e.g., sales)
- X= Independent variable (e.g., time)
- β_0= Intercept (starting point of the trend line)
- β_1 = Slope (rate of change over time)
- $\in$ = Error term (residuals)

Use the training dataset to fit the model by estimating the coefficients using an algorithm like Least Squares.

Step 5: Evaluate the Model

R-Squared (R^2): Measures how well the model explains the variation in Y.

Mean Squared Error (MSE) / Root Mean Squared Error (RMSE) measures accuracy.

Residual Analysis: Plot residuals to ensure they are randomly distributed.

Step 6: Predict future values using the trained model. And Plot the initial data points and place the trend line on top of them.

Step 7: Interpret the Trend Line

If the slope (β_1) is:

- Positive → Increasing trend.
- Negative → Decreasing trend.
- Near zero → No significant trend.

Step 8: Perform Linear Regression for Both variables

Equations:

$$Y = \beta_0 + \beta_1 X + \epsilon_1 \text{ (variable1 trend)}$$

$$Y = \beta_0 + \beta_2 X + \epsilon_2 \text{ (variable2 trend)}$$

- β_1 and β_2 are slopes
- ϵ_1 and ϵ_2 are error terms

Step 9: Compare the regression slopes

If $\beta_1 > \beta_2$ – variable1 is increasing

If $\beta_1 < \beta_2$ – variable2 is increasing

Check R-squared values

Higher R^2 – A stronger linear trend

Compare R^2 for both the models to see which has a better trend fit.

Calculate Compound Growth Rate (CAGR) for both

$$\text{CAGR} = \left(\frac{V_{final}}{V_{initial}}\right)^{\frac{1}{n}} - 1$$

Where V_{final} and $V_{initial}$ are the last and first year values.

Compare CAGR of both variables

Step 10: Compare the slopes visually using a bar chart.

3.3 GROWTH RATE ANALYSIS

Growth rate is a fundamental concept used in economics, finance, business, and science to measure how a particular quantity changes over time. It facilitates trend analysis, forecasting, and strategic decision-making. Growth rate measures how much a value has increased or decreased over a specific time period. It can be computed for a number of variables, and is typically given as a percentage.

$$\textbf{Growth rate} = \left(\frac{Final\ value - Initial\ value}{Final\ value}\right) \times 100$$

3.3.1 Compound Annual Growth Rate

The average annual growth rate of a firm, investment, or other value over a given time period, assuming it rises steadily each year, is known as the compound annual growth rate, (CAGR). CAGR takes compounding into account, which means that growth is applied to both the beginning value and the cumulative growth over time, in contrast to simple growth rate, which only takes into account the absolute change.

$$CAGR = \left(\frac{Final\ value}{Initial\ value}\right)^{\frac{1}{n}} - 1$$

Where:

- Final Value (FV) = Value at the end of the period
- Initial Value (IV) = Value at the start of the period
- n = Number of years

The study examines the growth of Haryana's textile industry over a decade, focusing on cotton production, cultivated area, and export of handloom, handicrafts, and raw cotton. Statistical techniques like correlation, regression, CAGR, and trend analysis were used to analyze the data. A strong positive correlation was found between cotton cultivation and production, with a CAGR of 7% over the 10-year period. Haryana was identified as the best-performing state in the region, surpassing Northern India's 5%. Handloom and handicraft export trends showed a CAGR of 10% for handloom exports, with an absolute growth of 264%. Handicraft exports showed a CAGR of 15% and an absolute increase of 415%. Raw cotton export data showed an unprecedented absolute growth of 4842%, the highest among all textile segments in Haryana. The findings suggest substantial growth in Haryana's textile sector, with potential for employment generation, as the Haryana Textile Policy 2019 aims to create over 50,000 jobs. Darji, (2021).

This research article explores handloom cloth production in India and examines the sector's trends over the past 35 years. To achieve this, statistical data from 1980–81 to 2014–15 has been analyzed. A key objective of the study is to assess the impact of economic reforms introduced in the 1990s on handloom production. Specifically, the study aims to (a) analyze production trends during the economic reform period from 1980–81 to 2014–15 and (b) evaluate the reforms' effects on the sector. The research relies on secondary data collected from official sources, including the Ministry of Textiles, the Khadi and Village Industries Commission, and the Office of the Textile Commissioner in Mumbai. The data has been analyzed using statistical methods such as Annual Growth Rate (AGR), Compound Annual Growth Rate (CAGR), and Arithmetic Mean ($\overline{x}$). MS Excel has been used for data estimation and analysis. Sankarakumar (2016).

Steps in growth rate analysis

Step 1: Collect the data make the initial value , final value and total number of years.

Step 2: Split the data into 3 groups

Step 3: Calculate annual growth rate for each year

$$\mathbf{AGR} = \left(\frac{\textit{Final value} - \textit{Initial value}}{\textit{Final value}} \right) \times \mathbf{100}$$

Step 4: Calculate Compound Annual Growth Rate for each group separately

$$\boldsymbol{CAGR} = \left(\frac{\textit{Final value}}{\textit{Initial value}}\right)^{\frac{1}{n}} - \mathbf{1}$$

CHAPTER 4
ANALYSIS

4.1 DATA DESCRIPTION

For the purpose of the study, the data was collected from the Handloom Weaver's Co-operative Socity Ltd. no. H47 Chendamangalam. The data consist of yearly data of yearly data value of production and sales of handloom clothes over 5 decades (1973-2023).

4.2 INTRODUCTION ABOUT THE CHAPTER

This analysis study involves three techniques, ARIMA modeling is used for forcasting production and sales , Linear regression is used for identifying the trend in production and sales and predicting which variable is best for forecasting and Growthrate Analysis to analyse the growth rate of production and sales.

ARIMA is a technique designed to analyze non-seasonal patterns in time series data. This model relies on historical trends and patterns to generate future predictions. ARIMA modeling assumes that the data is both stationary and univariate. To analyze growth rates, The data is segmented into groups, and the annual growth rate for each year is calculated. Finally, the CAGR is determined separately for each group to assess long-term trends, providing a more accurate measure of consistent growth. Linear regression is used to study the relationship between two variables. It is used to predict the future trend and by using CAGR the comparison of trend is calculated.

4.3 GROWTH RATE ANALYSIS

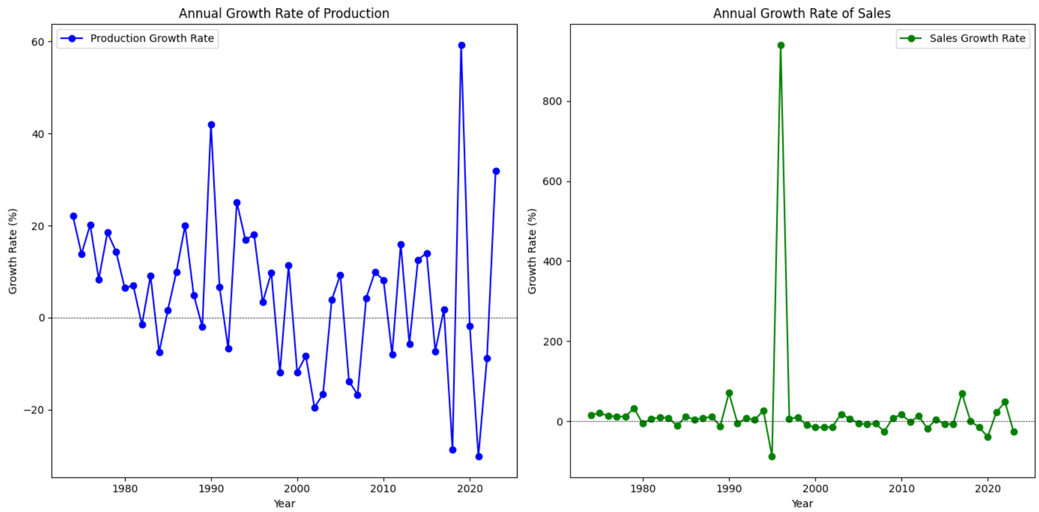

Figure 4.3.1

Here shows a high growth during 1990-2000

4.3.1 COMPOUNT ANNUAL GROWTH RATE ANALYSIS

This study is classified into three time periods and they are as follows:

(1)handloom cloth production in period (1973 to 1989) (2) handloom cloth production in period (1989to 2006) (3) handloom cloth production in period (2006 to 2023). First period contains 16 years data and other period has 17 years data.

Table 4.3.1

SL NO	YEAR	PRODUCTION	AGR	CAGR
1	1974	1575203	22.07	8.76%
2	1975	1793131.36	13.83	
3	1976	2155000.00	20.18	
4	1977	2335044.85	8.35	
5	1978	2767269.61	18.51	
6	1979	3165105.08	14.38	
7	1980	3371082.52	6.51	
8	1981	3605056.29	6.94	
9	1982	3549485.13	-1.54	
10	1983	3872553.95	9.10	
11	1984	3582572.56	-7.49	
12	1985	3640562	1.62	
13	1986	4004195.58	9.99	
14	1987	4804433.42	19.98	
15	1988	5042515.43	4.95	
16	1989	4942658.9	-1.98	
17	1990	7016461.54	41.96	2.17%
18	1991	7478909.63	6.6	
19	1992	6974349.21	-6.74	
20	1993	8724337.76	25.09	
21	1994	10193583.35	16.84	
22	1995	12034713.69	18.06	
23	1996	12439796.2	3.36	
24	1997	13654298.24	9.76	
25	1998	12030328.02	-11.9	
26	1999	1392641.3	11.32	

27	2000	11808147.64	-11.83	
28	2001	10825932.95	-8.32	
29	2002	8714429.8	-19.50	
30	2003	7271062.05	-16.56	
31	2004	7550805.75	3.84	
32	2005	8255058.55	9.33	
33	2006	7115165.67	-13.81	
34	2007	5926247.1	-16.71	
35	2008	6180026.25	4.28	
36	2009	6789408.65	9.86	
37	2010	7346664.4	8.21	
38	2011	6758096.75	-8.01	
39	2012	7839438.5	16	
40	2013	7392596	-5.7	
41	2014	8322272.75	12.57	
42	2015	9491121.75	14.04	0.99%
43	2016	8802067.75	-7.26	
44	2017	8955612.57	1.74	
45	2018	6392428.15	-28.62	
46	2019	10180773.44	59.26	
47	2020	9996890.74	-1.80	
48	2021	6982280.1	-30.15	
49	2022	6372434.7	-8.73	
50	2023	8407304.75	31.93	
TOTAL	**AVERAGE**	**6923764.77**	**5.08**	

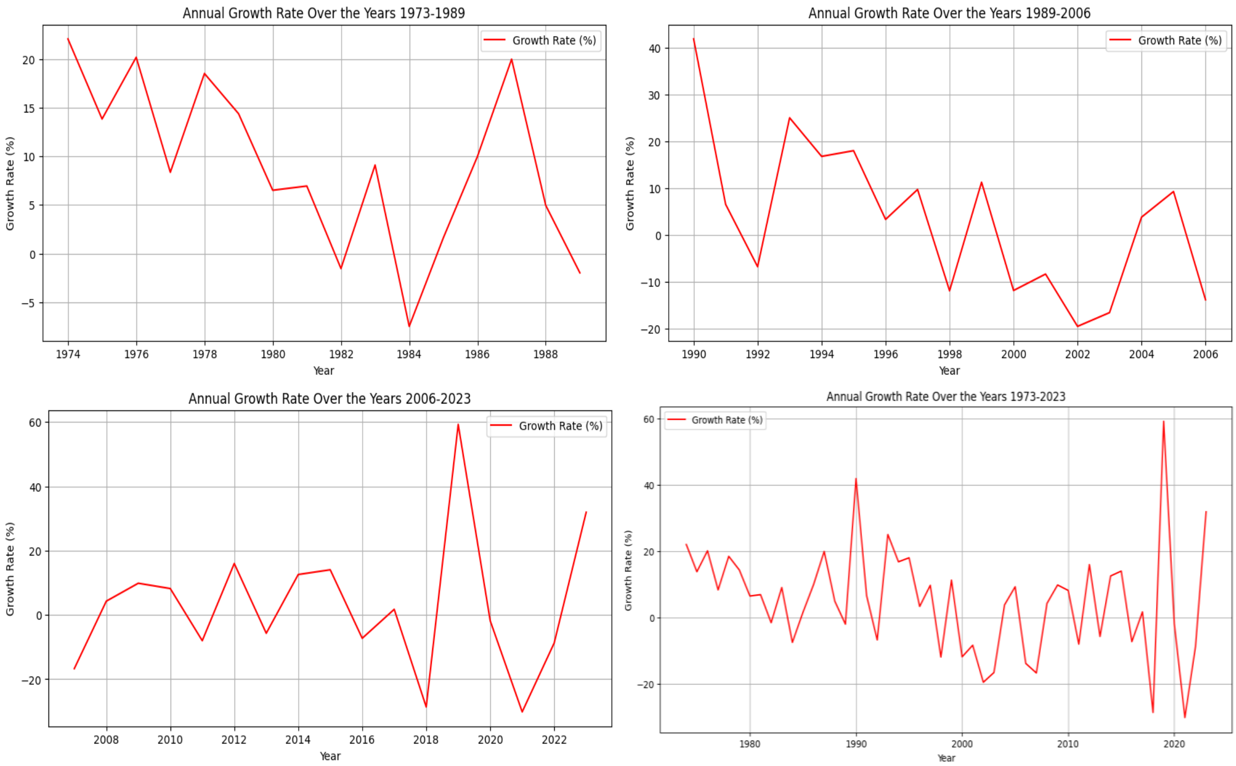

Figure 4.3.2

The handloom cloth industry in Chendamangalam has seen a shifting growth pattern over the years. From 1973 to 1989, production flourished with a strong 8.76% annual growth rate. However, this momentum slowed to 2.17% between 1989 and 2006 and dropped even further to just 0.99% from 2006 to 2023. While the 1990s marked the industry's peak growth, recent years have been marked by stagnation and fluctuations. This steady decline suggests that without timely intervention, the industry may struggle to sustain itself in the long run.

4.4 LINEAR REGRESSION

4.4.1 PREDICT TREND

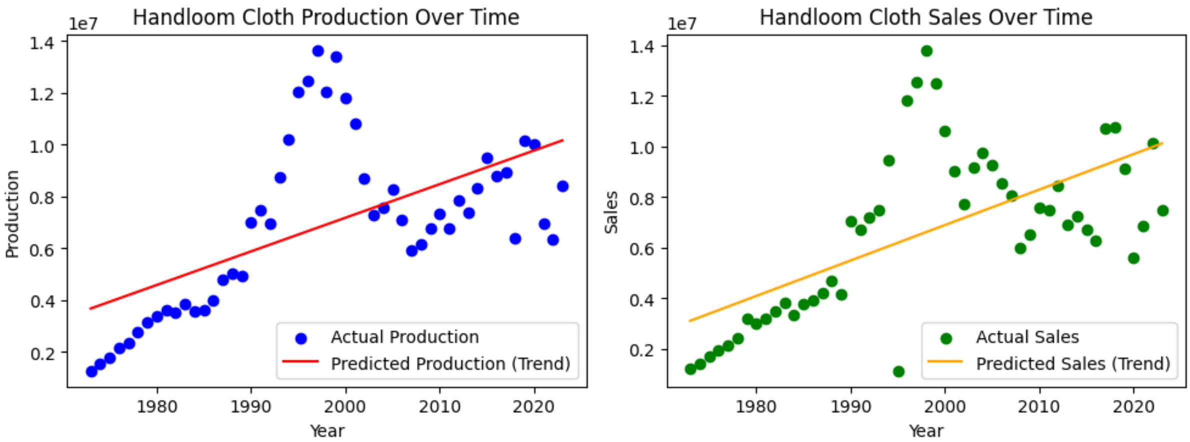

Figure 4.4.1

4.4.2 COMPARISON

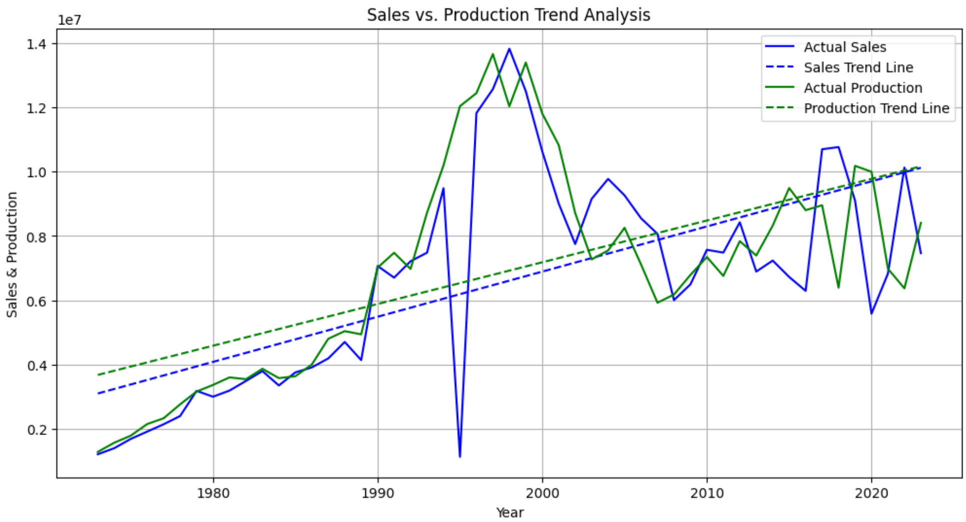

Figure 4.4.2

Sales Trend:- Slope = 140316.46

$R^2 = 0.405$

CAGR = 3.69%

Production Trend:- Slope = 129668.70

$R^2 = 0.358$

CAGR = 3.82%

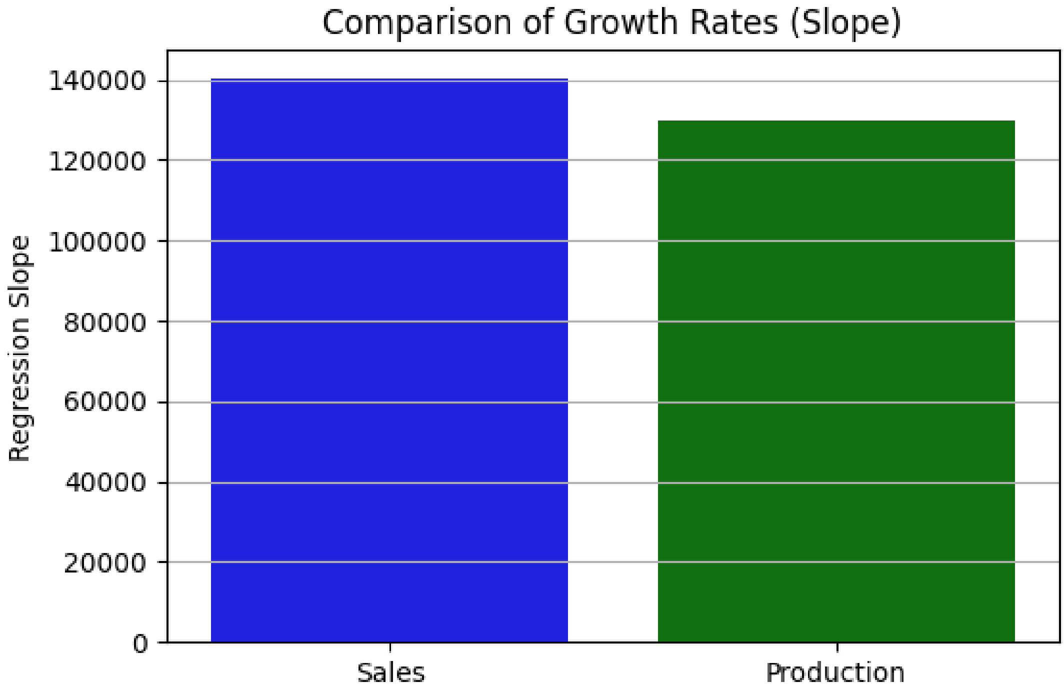

Figure 4.4.3

The analysis shows a steady upward trend in both handloom cloth production and sales. Sales are growing slightly faster, with a slope of 140,316.46 units and a CAGR of 3.69%, compared to production, which has a slope of 129,668.70 units and a CAGR of 3.82%. However, the moderate R^2 values (0.405 for sales and 0.358 for production) suggest that other factors, like market demand and policies, may also be influencing these trends. While the growth indicates increasing demand, further research is needed to understand the broader impact of external factors.

4.5 ARIMA MODEL

4.5.1 PRODUCTION

4.5.1.1 Time series plot

The time series plot of production of handloom cloth is given in Figure 4.5.1

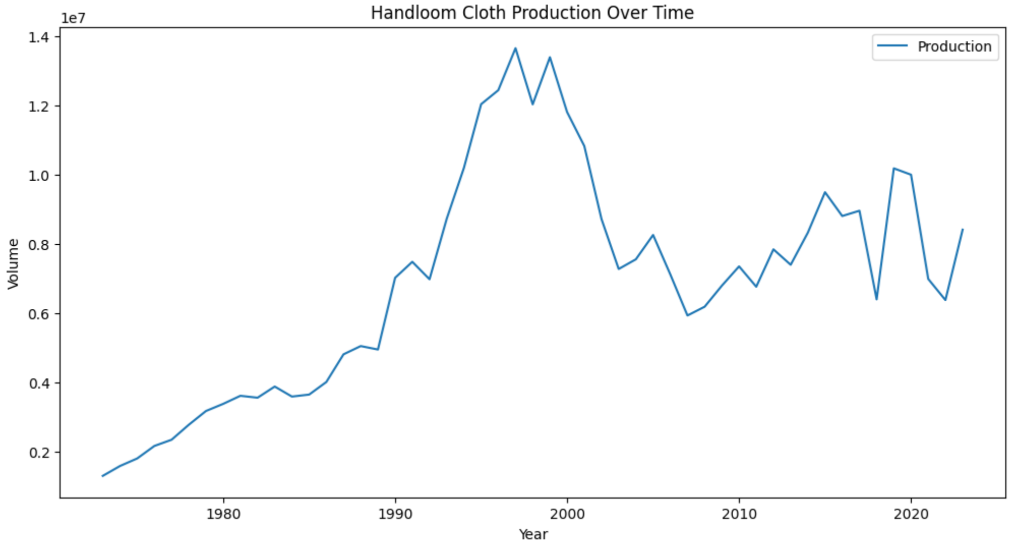

Figure 4.5.1

4.5.1.2 Decomposition of time

The second step is to perform seasonal decomposition to capture the trend, seasonal and random components of time series. Figure 4.5.2 depicts the seasonal plot.

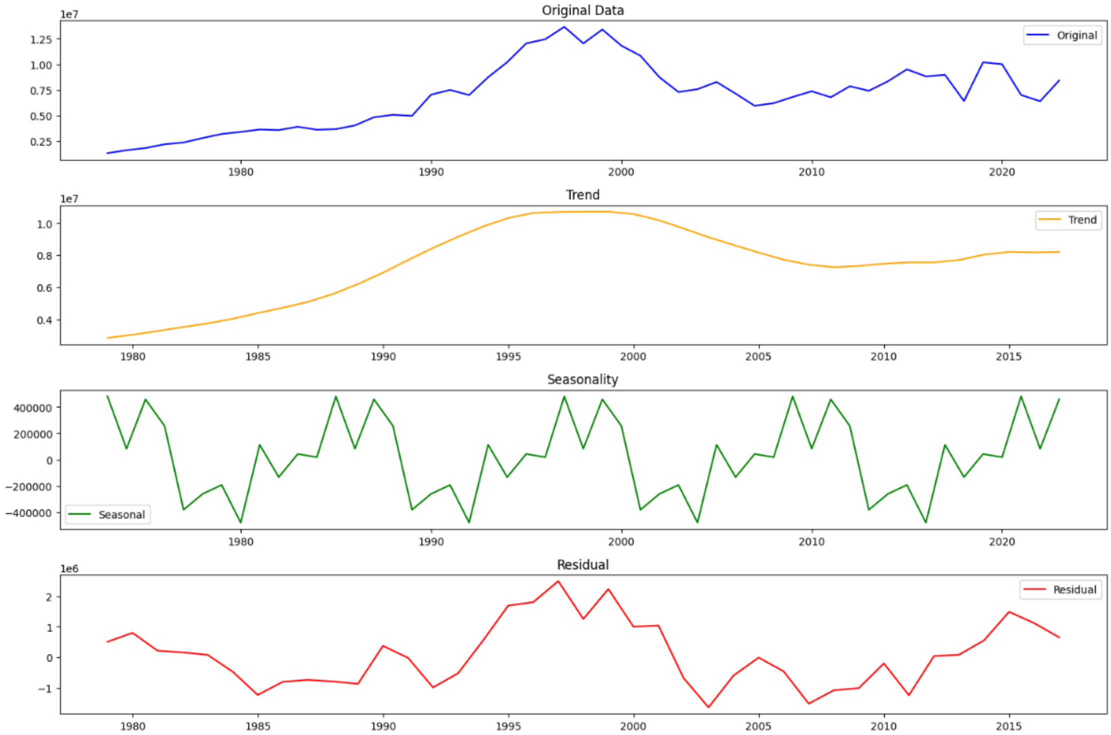

Figure 4.5.2

4.5.1.3 Deseasonalized Production

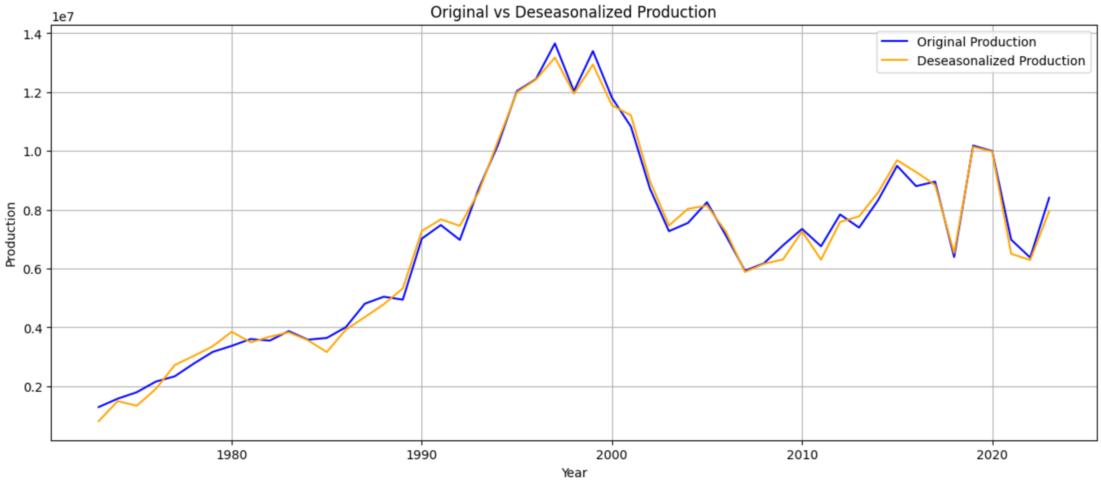

Figure 4.5.3

4.5.1.4 Stationarity check using Augmented Dickey-Fuller Test

To test the time series data for stationarity using ADF test, follows a hypothesis testing approach.

The null hypothesis H_0 is given by,

H_0: The series is non stationary.

The alternative hypothesis H_1 is given by,

H_1: The series is stationary

Results obtained

ADF Statistic: -2.5039641028528625

p-value: 0.11451279263819664

The p-value is greater than 0.05, so we fail to reject the null hypothesis.

The series is not stationary

Hence we perform n order differencing until we get time series stationary in both cases We perform differencing with n = 1 Now we again check stationarity using ADF test.

Here we test the hypothesis,

The null hypothesis H_0 is given by,

H_0: The series is non stationary.

The alternative hypothesis H_1 is given by,

H_1: The series is stationary

Results obtained

ADF Test Results:

ADF Statistic: -7.08845796778615

p-value: 4.4744127410237193e-10

Critical Values:

1%': -3.5714715250448363

5%: -2.922629480573571

10%: -2.5993358475635153

The p-value is less than 0.05, so we reject the null hypothesis. The differenced production series is stationary

Figure 4.5.4 shows the differenced production

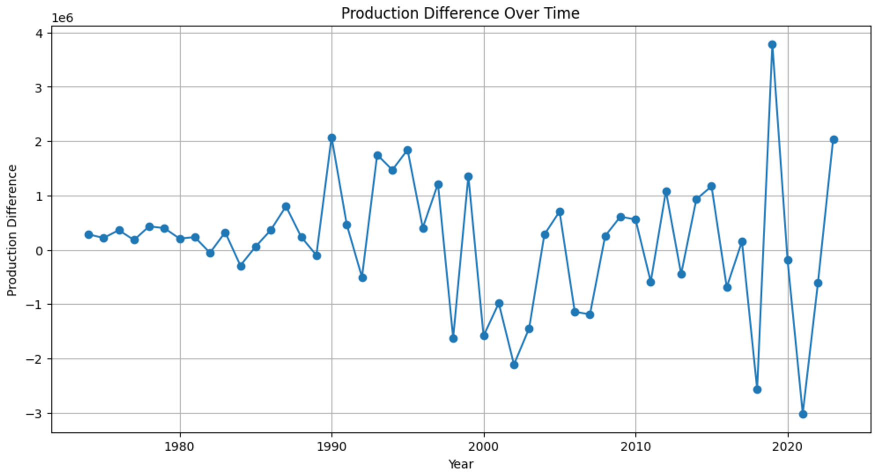

Figure 4.5.4

4.5.1.5 Autocorrelation and Partial Autocorrelation Function

Next step in Time Series Analysis is to plot and examine Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). ACF &PACF Plot is given in Fig 4.5.5

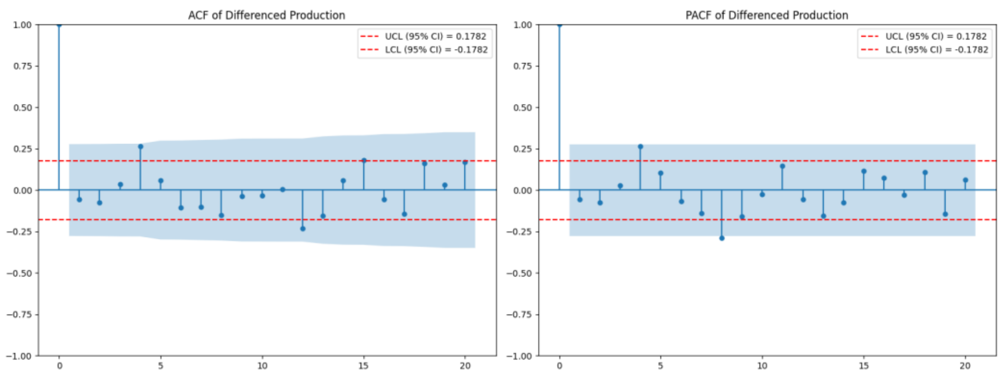

Figure 4.5.5

4.5.1.6 ARIMA Model for Production

In this step we choose the best model for forecasting the values. It is done by choosing one model from all possible models according to Akaike Information Criterion (AIC). The model with lowest AIC value is chosen as the best model. Below Table 4.5.1 shows the possible models with their AIC values.

Table 4.5.1

SL.NO	ARIMA MODEL (p,d,q) x (P,D,Q)	AIC
1	(0, 0, 0) x (0, 0, 0)	1427.797
2	(0, 0, 1) x (0, 0, 0)	1292.072
3	(0, 0, 2) x (0, 0, 0)	1280.230
4	**(1, 0, 0) x (0, 0, 0)**	**1224.465**
5	(1, 0, 1) x (0, 0, 0)	1225.487
6	(1, 0, 2) x (0, 0, 0)	1225.949

Here the best model is ARIMA (1, 0, 0) x (0, 0, 0) with AIC value 1224.4654

4.5.1.7 Diagnostic checking

Diagnostics checking is performed for confirming the validity, effectiveness and reliability of statistical models. The main objective of it is to choose the right and best model.

Ljung-Box test

Null Hypothesis (H_0): The residuals of the model are independently distributed

Alternate Hypothesis (H_1): The residuals of the model are not independently distributed.

The Ljung-Box test results of production suggest the following:

Test Statistic : 23.02985

P-value: 0.287331

P=0.287331 is greater than 0.05, It suggests that the residuals are uncorrelated. Thus the model is a good fit.

Shapiro-Wilk Test for Normality

Null Hypothesis H_0: The data is normally distributed.

Alternative Hypothesis H_1: The data is not normally distributed.

Shapiro-Wilk Test result for Normality of production:

Test Statistic: 0.961990664225231

P-value: 0.195812981950875

P=0.195812981950875 is greater than 0.05, fail to reject H_0. The data proves that it is normally distributed.

Diagnostic plot is given in Figure 4.5.6

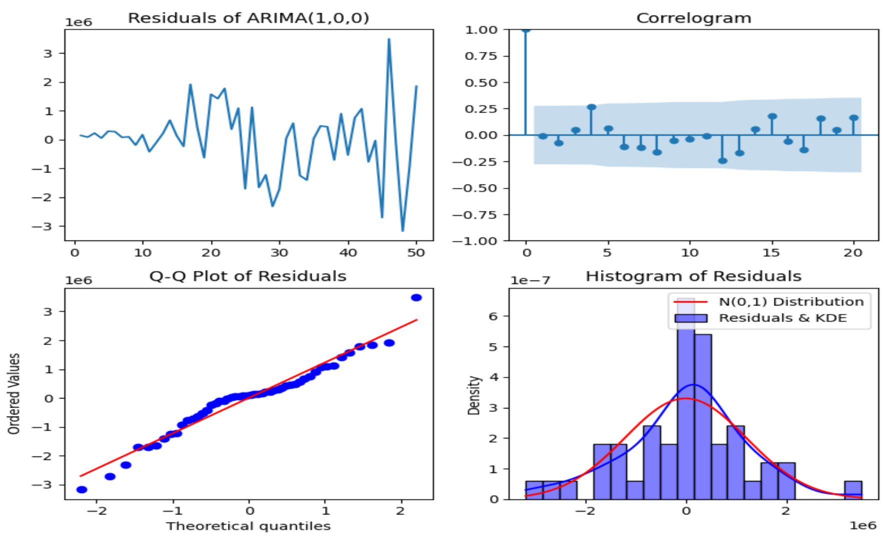

Figure 4.5.6

From Q-Q plot, it is clear that most of the residuals are on the same line and standard residual are normally fitted.

4.5.1.8 Forecasting the Future Values

The forecasted Production of Handloom cloth for 10 years from 2024 to 2034 is given in Table 4.5.2

Table 4.5.2

YEAR	FORECASTED PRODUCTION	LCL	UCL
2024-2025	7365549	5515213	9215886
2025-2026	7339556	4773223	9905889
2026-2027	7314574	4231245	10397900
2027-2028	7290565	3797036	10784090
2028-2029	7267492	3433880	11101100
2029-2030	7245316	3122436	11368200
2030-2031	7224004	2850909	11597100
2031-2032	7203522	2611413	11795630
2032-2033	7183837	2398334	11969340
2033-2034	7164918	2207486	12122350

The Figure 4.5.8 shows the graph of forecasted production from 2024 – 2034

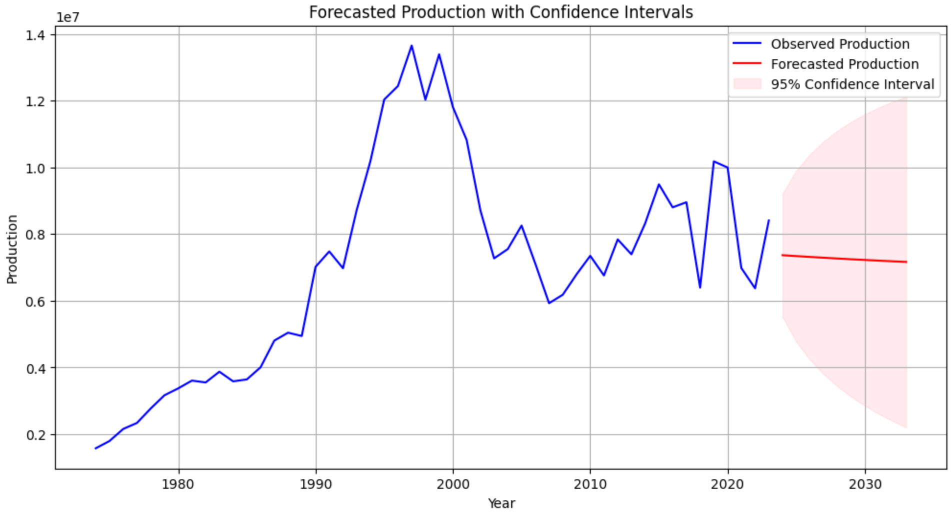

Figure4.5.7

4.5.2 SALES

4.5.2.1 Time series plot

The initial step in time series is to draw a time series plot. The time series plot of sales is given in Fig 4.5.8

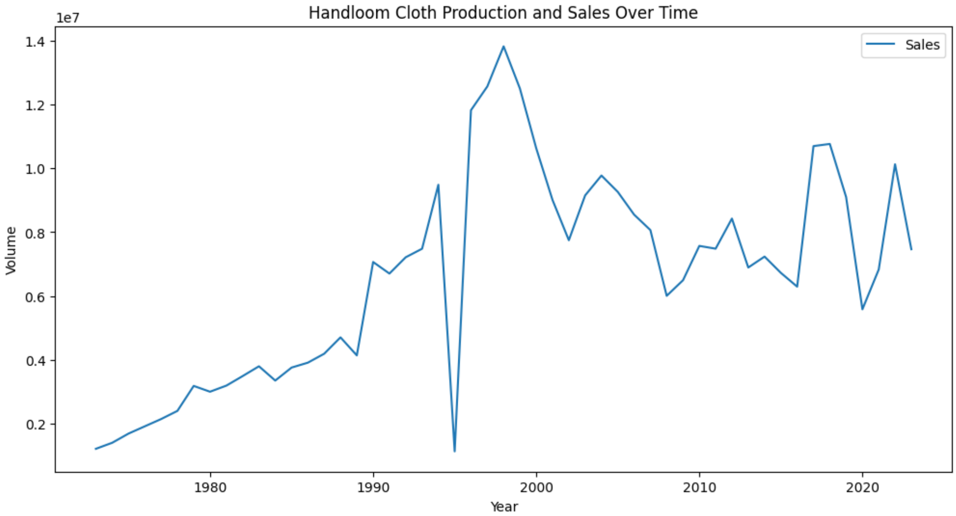

Figure 4.5.8

4.5.2.2 Decomposition of time

The second step is to perform seasonal decomposition to capture the trend, seasonal and random components of time series. Plot the seasonal plot. Fig 4.5.9 depicts the seasonal plot

Figure 4.5.9

From the fig.4.5.9, it can conclude that data has no seasonality

4.5.2.3 Stationarity check using Augmented Dickey-Fuller Test

To test the time series data for stationarity using ADF test, follows a hypothesis testing approach.

The null hypothesis H_0 is given by,

H_0: The series is non stationary.

The alternative hypothesis H_1 is given by,

H_1: The series is stationary

Results obtained

ADF Statistic: -2.993789974159436

p-value: 0.03547842246342844

The p-value is less than 0.05, so we reject the null hypothesis. The series is stationary.

4.5.2.4 Autocorrelation and Partial Autocorrelation Function

Next step in Time Series Analysis is to plot and examine Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). ACF &PACF Plot is given in Fig 4.5.10

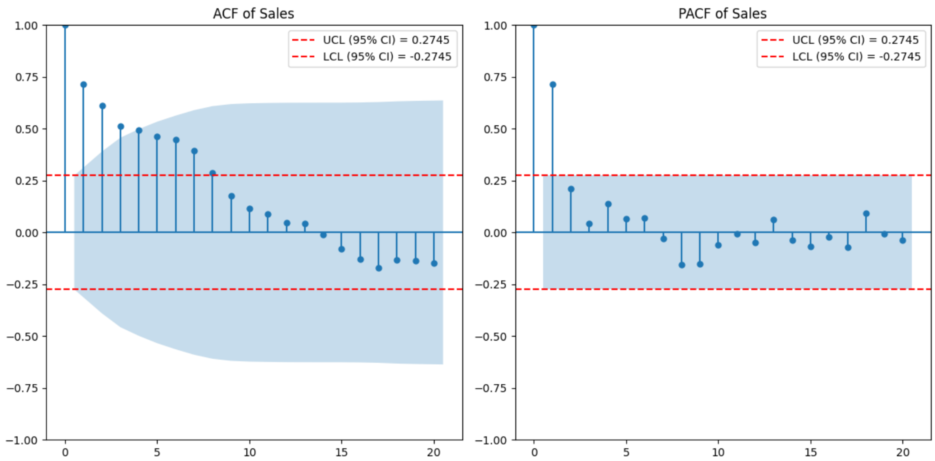

Figure 4.5.10

4.5.2.5 ARIMA Model for Sales

In this step we choose the best model for forecasting the values. It is done by choosing one model from all possible models according to Akaike Information Criterion (AIC). The model with lowest AIC value is chosen as the best model. Table 4.5.3 shows the possible models with their AIC values.

Table 4.5.3

SL NO	ARIMA MODEL (p, d, q) x (P, D, Q)	AIC
1	(0, 0, 0) x (0, 0, 0)	1430.434
2	(0, 0, 1) x (0, 0, 0)	1308.7590
3	(0, 0, 2) x (0, 0, 0)	1301.7290
4	**(0, 0, 3) x (0, 0, 0)**	**1298.649**
5	(0, 0, 4) x (0, 0, 0)	1301.393
6	(0, 0, 5) x (0, 0, 0)	1308.358
7	(0, 0, 6) x (0, 0, 0)	1302.809

Here the best model is ARIMA (0, 0, 3) x (0, 0, 0) with AIC value 1298.646

4.5.2.6 Diagnostic checking

Diagnostics checking is performed for confirming the validity, effectiveness and reliability of statistical models. The main objective of it is to choose the right and best model.

Ljung-Box test

Null Hypothesis (H_0): The residuals of the model are independently distributed

Alternate Hypothesis (H_1): The residuals of the model are not independently distributed.

The Ljung-Box test results of production suggest the following

Test Statistic : 12.537154

P-value: 0.250713

P=0.250713 is greater than 0.05, It suggests that the residuals are uncorrelated. Thus the model is a good fit.

Diagnostic plot is given below

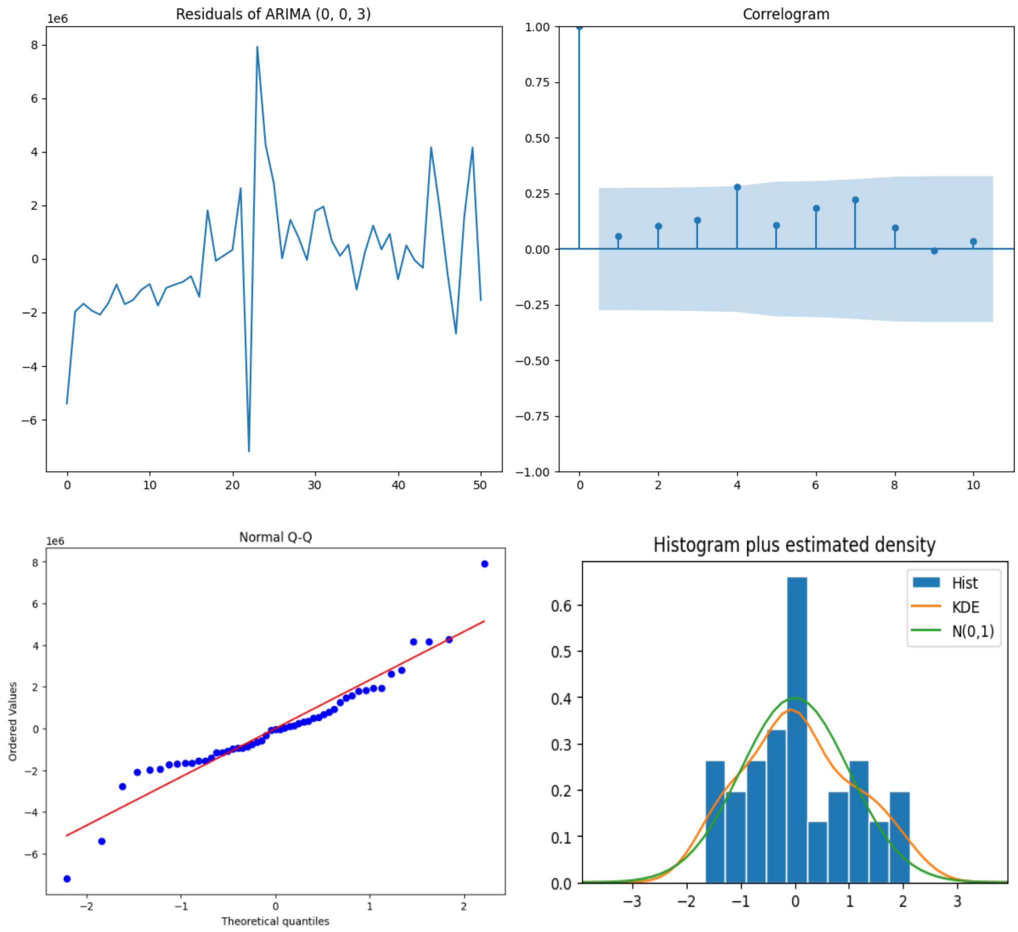

Figure 4.5.11

From Q-Q plot, it is clear that most of the residuals are on the same line and standard residual are normally fitted.

4.5.2.7 Forecasting the Future Values

The forecasted Sales of Handloom cloth for 10 years from 2024 to 2034 is given in Table 4.5.4

Table 4.5.4

YEAR	FORCASTED SALES	LCL	UCL
2024-2025	8651023	4447460	12854591
2025-2026	8914912	4711349	13118470
2026-2027	9178801	4975238	13382363
2027-2028	9442689	5239126	13646253
2028-2029	9706578	5503015	13910140
2029-2030	9970467	5766904	14174031
2030-2031	10234360	6030793	14437926
2031-2032	10498240	6294682	14701812
2032-2033	10762130	6558570	14965703
2033-2034	11026020	6822459	15229594

The Figure 4.5.12 shows the graph of forecasted sales from 2024 - 2034

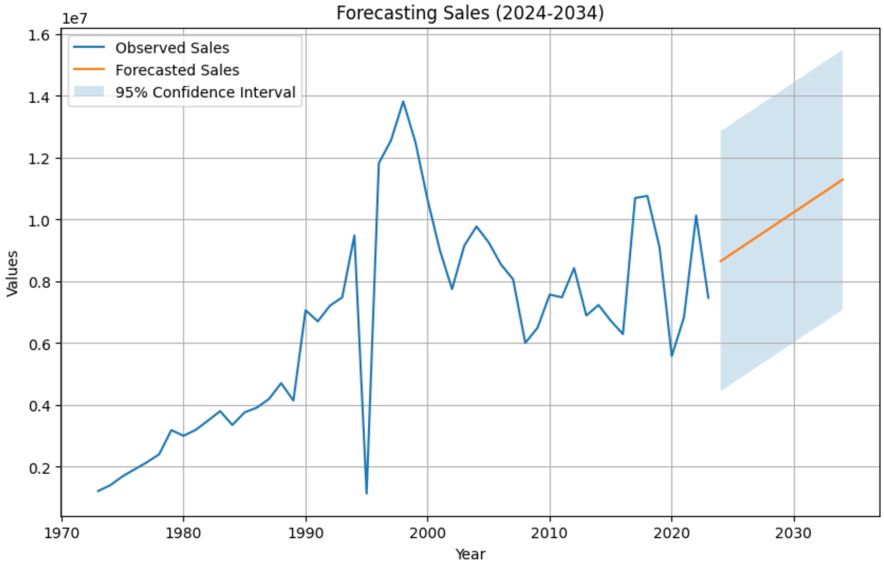

Figure 4.5.12

CONCLUSION

The analysis of handloom production and sales over three distinct time periods (1973-1989, 1989-2006, and 2006-2023) highlights a significant long-term trend. The Compound Annual Growth Rate (CAGR) analysis reveals a steady decline in growth rates, with the highest growth observed in 1973-1989 (8.79%), followed by 1989-2006 (2.17%), and a further decline in 2006-2023 (0.99%). This declining trend suggests that while the handloom industry initially experienced rapid expansion, growth has slowed down considerably in recent decades.

Linear regression analysis indicates a general upward trend in both sales and production, with a strong correlation between the two. However, occasional fluctuations suggest inconsistencies in supply and demand dynamics. The findings indicate that production is the most reliable predictor of future trends, reinforcing the need for stability in manufacturing processes to ensure sustained industry growth.

The ARIMA forecasting model suggests that sales of handloom fabrics are likely to experience robust growth between 2024 and 2034, signaling an increasing market demand. However, production is expected to either stabilize or witness a slight decline. This creates a critical opportunity for the industry to innovate and enhance operational efficiency. Addressing production challenges through technology adoption, improved supply chain mechanisms, and strategic policy interventions can help bridge the gap between demand and supply.

For long-term sustainability, the handloom sector must adopt a multifaceted approach to address the challenges posed by declining growth rates and fluctuating production patterns. First, optimizing production planning is essential to ensure consistency in output, minimizing volatility through strategic resource allocation, demand forecasting, and scalable manufacturing processes. Second, enhancing supply chain efficiency can strengthen distribution networks, improve logistics, and ensure the seamless flow of raw materials and

finished products, reducing production bottlenecks. Third, leveraging technology and innovation can drive productivity and quality improvements through automation, advanced weaving techniques, and sustainable production methods, enabling manufacturers to meet evolving market demands. Furthermore, market expansion through targeted policy support, including government incentives, financial assistance, and export promotion, can provide a competitive edge. Digital marketing, branding, and e-commerce integration will also play a crucial role in increasing consumer reach and engagement. By implementing these strategies, the handloom industry can not only bridge the gap between supply and demand but also establish a robust, sustainable framework for future growth, ensuring long-term viability in an increasingly competitive market.

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