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Development of a Web-Based Inventory Management System for Small Businesses

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Abstract

This work aimed at developing a web-based inventory management model for application in firms where data on inventory collection, storage, retrieval, analysis, and good management decisions are needed for well-informed management policy-making and for monitoring the overall performance of the establishment. This study applied an autoregressive moving average (ARMA) time series modelling approach to generate a model for forecasting monthly production quantity in Unizik Plastic Unit. A web-based inventory system for easy recording, visualization, and monitoring of inventory in the unit was developed using the My structured query language (MySQL) database. The generated ARMA model, economic order quantity model, suppliers, customers, and other useful information were built into an inventory management database system to enable continuous data collection, storage and quick access to inventory data on the target establishment. The results showed that out of the various ARMA models examined, ARMA (1,1) model, with the lowest Bayesian information criterion, mean absolute percentage error and root mean square error, was selected as the most suitable model for forecasting of monthly quantity of production in the unit. The autocorrelation and partial autocorrelation plots of the residuals of the model and the Ljung-Box statistic revealed that the model is free from serial correlation, hence, adequate and fits well for the production data in the unit. The developed inventory management database system showed a great improvement in the inventory control in the unit over the existing inventory management practice in the unit.

Keywords: ARMA Model, Database system, Forecasting, Inventory management, Web-based Inventory.

1. Introduction

In any manufacturing industry, there must be some inventory of raw materials that will be processed, work-in-process which are still undergoing processing activities, and finished products for sales that are maintained to keep the factory running. Many organizations hold Inventory as the most important asset, representing as much as half of the company's expenses, or even half of the total capital investment (Render et al., 2016; Munyaka and Yadavalli, 2022). Effective and efficient management of inventories is crucial for the operational success, organizational performance, growth, and survival of such industries (Nemtajelai and Mbohwa, 2016; Munyaka and Yadavalli, 2022).

Poor management of any of the above inventories can result in both under and overstocking items (Onwurah, 2015; Plinere and Borisov, 2016). To be able to handle the problem of overstocking and understocking of raw materials, work-in-process, and finished product inventories, a prudent and proper inventory management approach must be in place (Godwin and Onwurah 2013a). The planned approach would help to determine what to order, when to order, how much to order, and how much to stock so that the costs involved in ordering and holding inventories are optimal without interrupting production and sales (Godwin and Onwurah, 2013a; Onwurah, 2015; Afolabi et al., 2017). According to Nemtajela and Mbohwa (2016), proper inventory management ensures a good balance between minimizing the total cost of inventory and maintaining the desired customer satisfaction level. This good balance has been missing in most of the small-scale industries in Nigeria.

One of the challenges small-scale industries in Nigeria have is the problem of not keeping proper records of the quantity of materials procured, the quantity utilized in production, the quantity of products sold, and the quantity remaining in stock. For them to survive, there is a need for them to keep track of inventory of what comes in and what goes out. Manual recordings, visualization, and assessment as still obtainable in some small and medium-scale industries in Nigeria cannot guarantee effective control of inventories in such industries. Decisions made on such manual recordings can be faulty sometimes. To be able to manage inventories properly, adequate inventory management system is needed in small and medium-scale manufacturing industries in Nigeria.

An Inventory management system allows employees or managers to track, record, and have an overview of product stocks that are coming in and out from the company inventory to ensure there is no unexpected low on stock or overstock (Wei et al., 2023). Godwin and Onwurah (2013a) employed classical (Q,R) inventory policy to determine the optimal inventory order quantity, optimum reorder point, and optimum safety stock for the raw materials that will ensure smooth operation in an industry. Wei et al. (2023) developed a web-based inventory management system that can provide better control and handling of product stock, customer orders, and order delivery information in small and medium enterprise retail stores in Malaysia. Although the above studies concluded that their systems were effective in the management of inventory in the selected industries, they did not consider demand forecasting in their inventory management systems. Inventory management systems must be able to incorporate forecasting, production planning, and control processes to ensure continuity between functions (Godwin and Onwurah, 2013b). To be able to solve the problems of understocking and overstocking in manufacturing industries, there is need for the accurate forecast of inventory requirements in such industries.

Forecasts are the basic input in the decision processes of operations management because they provide information on future demand. Demand forecasting has been a key approach to addressing uncertainties in inventory management (Onwurah, 2015; Seyedan and Mafakheri, 2020). A variety of statistical analysis techniques have been used for demand forecasting including time series analysis and regression analysis (Godwin and Onwurah 2013b; Wang et al., 2016; Seyedan and Mafakheri, 2020). Godwin and Onwurah (2013b) utilized regression analysis and time series analysis to generate accurate forecasting models for inventory management in polyvinyl chloride pipe manufacturing. The study considered inventory prediction without considering other control processes.

Developing a computer-based application that incorporates demand forecasting will help solve the problems of inventory management in small and medium-scale industries in Nigeria and will go a long way in ensuring that the industries remain competitive in this global competitive environment.

This study aims to develop a computer-based inventory management system for small-scale and medium-scale Plastic Producing Industries in Nigeria using the Nnamdi Azikiwe University Plastic Production Unit as a Case Study. This study pursued the following objectives: (1) to develop an autoregressive moving average (ARMA) model for inventory forecasting, (2) to develop a web-based inventory system using MySQL database for easier recording, visualization, and monitoring of the inventory in the organization. This web-based inventory management system utilizes ARMA time series modeling to generate accurate forecasts for small businesses. The system would provide a user-friendly, cost-effective solution for small businesses, enabling them to optimize their inventory management processes. This study is significant as combining the power of ARMA models with a web-based platform, would achieve inventory control excellence and enable the small businesses involved in this study to stay ahead in the competitive market.

2.0 Materials and Methods

2.1 Materials Used in this Study

Materials, tools, and other instruments used in this study include:

1. Sublime text: used in the construction and editing of the HTML, CSS JavaScript, and PHP codes for the application.
2. chrome: used for visualization of the website
3. XAMMP: used as a server or local host for the website
4. php: used to perform repetitive functions for different parts of the websites
5. Anaconda Jupyter: used as a platform/editor/notebook in which the code python codes are written.
6. Python: This is the language used to design the model
7. Sklearn: This is a library used to check the accuracy of the predicted value
8. Statsmodels: This is a library used to import ARIMA/SARIMAX model
9. Numpy: this is a library used to import mathematical calculating functions
10. Pandas: this is a library used to manage the dataset
11. Computer system with the following minimum specifications:
    a. A Repository: sourceforge.net/projects/xampp
    b. Operating system: Windows 8 or newer, 64-bit macOS 10.13+, or Linux, including Ubuntu, RedHat, CentOS 6+, and others.
    c. System architecture: Windows- 64-bit x86, 32-bit x86; MacOS- 64-bit x86; Linux- 64-bit x86, 64-bit Power8/Power9
    d. Processor: at least 2 CPU cores.
    e. Windows ram: 2GB RAM
    f. Storage: Minimum 5 GB disk space to download and install.

2.2 Data Sources

In this study, 30-month production data, from July 2020 to December 2022, were collected from Unizik Plastic Production Unit. Other information used in this study was collected through direct observation of production processes and interviews of the workers in the company.

2.3 Methods Used

2.3.1 System design and development

The web-based inventory management system was designed and developed using a user-centered approach, focusing on simplicity, ease of use, and scalability. The system consists of three main modules:

1. Data Input Module: This module allows users to input historical inventory data, including stock levels, demand, and lead times. The data are stored in a secure database for further processing.

2. Forecasting Module: This module utilizes ARMA time series modeling to generate accurate forecasts of future inventory levels.

3. Reporting and Visualization Module: This module provides users with a dashboard to view forecasts, track inventory levels, and receive alerts when inventory levels are low. The module also generates reports on forecast accuracy, inventory turnover, and other key performance indicators.

The system was developed using HTML, CSS, and JavaScript for the front end, and Python with Flask framework for the back end. The database management system used is MySQL. The ARMA model was implemented using the statsmodels library in Python.

To ensure scalability and reliability, the system was deployed on a cloud-based server using Amazon Web Services (AWS). The system is accessible via a web browser, making it easy for small businesses to access and manage their inventory from anywhere.

In terms of security, the system implements user authentication and authorization, data encryption, and regular backups to ensure data integrity and confidentiality.

2.3.2 Autoregressive Moving Average (ARMA)

The data collected were analyzed using the autoregressive moving average (ARMA) modeling technique. An ARMA (p,q) model is a combination of autoregressive, AR (p), and moving average, MA(q) models suitable for stationary univariate time series modeling. For nonstationary time series, ARIMA (p,d,q), which combines autoregressive (AR) and moving average (MA) models, explicitly includes differencing in the formulation of the model suitable for univariate time series analysis, is used (Ihueze and Onwurah, 2018a; 2018b). In this study, ARMA was used instead of ARIMA because the time series data collected was stationary. Hence, no differencing was required for generating the time series model.

The general process for ARMA models is as follows:

- ✓ Visualize the Time Series Data
- ✓ Plot the Correlation and Auto-Correlation Charts
- ✓ Construct the ARMA Model based on the data
- ✓ Use the model to make predictions

The 30 months' time series data collected were plotted to visualize the data. The data were subjected to a stationarity test to ascertain whether stationary or nonstationary. A stationary time series is a time series whose mean, variance, and autocorrelation are constant over some time. The stationarity of the time series used in this study was checked using the time series plots of the data and the Augmented Dickey-Fuller (ADF) test. The ADF test gives various values for identifying stationarity. The null hypothesis assumes a test statistic (TS) as non-stationary. It comprises a TS and some critical values for some confidence levels. If the TS is less than the critical values, the null hypothesis is rejected and that series is said to be stationary. The ADF test also gives a *p*-value. According to the null hypothesis, lower values of *p* are better. The result of the ADF was confirmed using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

After achieving a stationary time series, the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) were used to figure out the order of AR, and MA values respectively in ARMA models. The end slope of each diagram represents the value at point *x* in the plot.

The general form of the ARMA (p,q) model is given by (Hipel and McLeod, 1994; Cochrane, 1997):

$$y_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i y_{t-1} + \sum\nolimits_{j=1}^{q} Q_j \varepsilon_{t-1} \qquad (1)$$

ARMA (p,q) model can be written using lag operator notation as (Hipel and McLeod, 1994):

$$\varphi(L)y_t = \theta(L)\varepsilon_t \tag{2}$$

Where y_t is the actual value
ε_t is random error (white noise) at a period t,
φ_i $(i = 1,2, \ldots p)$ are autoregressive model parameters and p is the order of the autoregressive part,
θ_j (j =1, 2,...q) are the moving average model parameters and q is the order of the moving average part,

$$\varphi(L) = (1 - \varphi_1 L - \varphi_2 L^2 - \cdots - \varphi_p L^p) \tag{3}$$

$$\theta(L) = \left(1 + \Theta_1 L + \Theta_2 L^2 + \cdots + \Theta_q L^q\right) \tag{4}$$

L is lag operator defined by $L^k y_t = y_{t-k}$ (5)

The statistically significant and adequate ARMA (p, q) model for time series modeling and forecasting is formulated following the Box-Jenkins methodology (Box and Jenkins 1976). Box and Jenkins (1976) proposed a three-step iterative process of model identification, parameter estimation and diagnostic checking to determine the best parsimonious model. The three-step iterative process proposed by Box and Jenkins (1976) was followed in this study.

2.3.3 The Use Case Diagram for the Proposed Inventory Management System

Use case diagrams are a type of dynamic behaviour view in Unified Modelling Language that are used to specify a set of actions that a system must carry out in cooperation with one or more external users (actors) (Nwamekwe et al., 2020; Mgbemena et al., 2018). Fig. 3 shows the use case diagram for the inventory management system being developed. The inventory staff can access manage supplier, stock control, view report and manage orders. The owner/Admin can access manager user, manage supplier, stock control, view report and manage orders. The customer can access view order product and the supplier can access manage supplier.

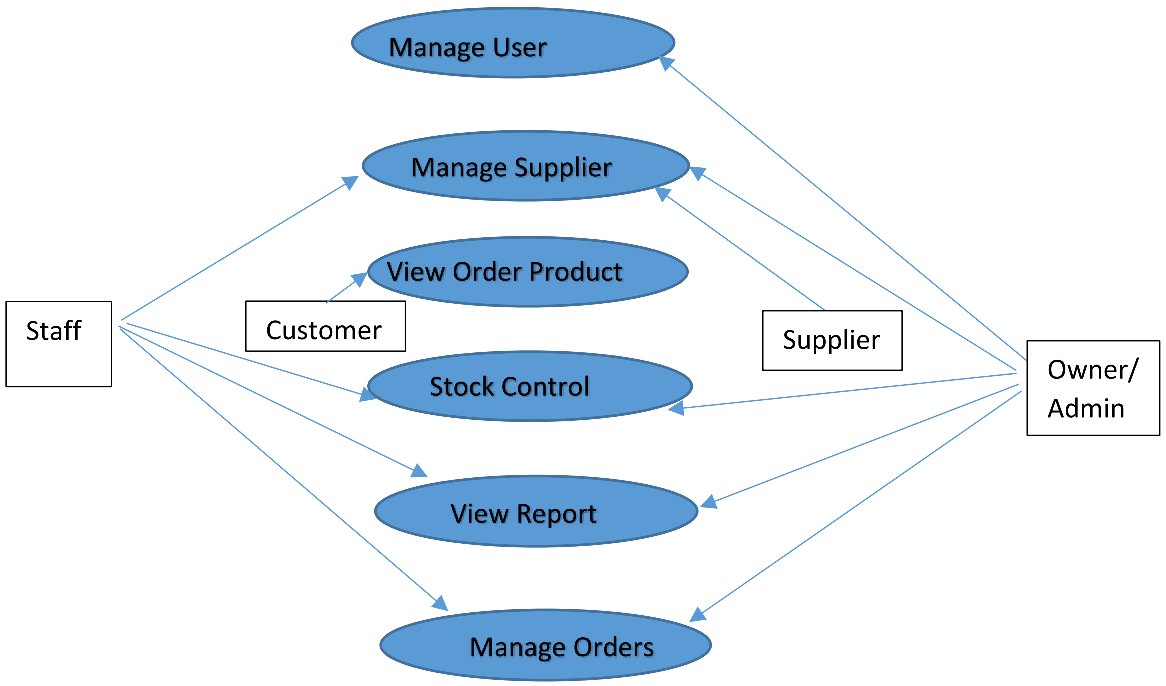

Figure 1: Use Case Diagram for the Inventory Management System

2.3.4 Development of parts of the inventory management application

2.3.4.1 Functional Requirements of the Inventory Management System

The functional requirements of the system and its components are explained in this subsection.

A. ***Design of the homepage***: A Homepage that shows the pictorial view and some basic information about the application was designed using web design tools and codes. The design of the homepage is shown in Fig. 2.

Figure 2: Model/Application homepage

B. **Creating the login page:** This is the second stage of creating the inventory management system. This aim is to facilitate privatization so that only users who are registered to the company will have access to the inventory system. This consists of HTML, CSS, and PHP for formatting, designing, and passing in functions during the logging process. The designed login page is represented in Fig. 3.

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Figure 3: The Application's login page

C. **Creating the dashboard:** The dashboard is for the user’s interactions with the application. This application component is designed and coded so that when a user creates an account, the user can navigate, control, and personalize various inventory management system features to suit departmental needs and help maintain the company's transaction records in an organized manner. See Fig. 4.

The dashboard was designed for simple features and easy usage. It consists of various data input sources such as:

i. **Dashboard page:** it contains different visualizations of product management such as order status, delivery time, etc.
ii. **User name input text:** this enables the user to manage the number of users needed
iii. **Supplier name input text:** this enables the user to manage its product supplier information
iv. **Purchase order input text:** this section manages the re-order process and its delivery status
v. **Receipt request button:** this object activates the generation of transaction receipts based on the user's choice.

Figure 4: The dashboard

D. **Design of the database:** The database is structured in a way that input data are stored in data sets tables. Each table has a unique identifier for each record set known as the primary key.

E. **Design of tables and their relationships:** The database tables are linked or joined in some ways that enable data stored in the database to be retrieved through queries. The designed tables with their imputable data type are presented in Tables 1 to 6 while their relationships are depicted in Fig. 5.

Table 1: Structure of the order product

Field name	Data type
Id	Int
Supplier	Int
Product	Int
Quantity ordered	Int
Quantity received	Int
Quantity remaining	Int
Status	Varchar
Batch	Int
Created by	Int
Created at	Datetime
Updated at	Datetime

Table 2: Structure of the product

Field name	Data type
Id	Int
Product name	Int
Description	Varchar
Image	Varchar
Created by	Int
Created at	Datetime
Updated at	Datetime

Table 3: Structure of the stock

Field name	Data type
Id	Int
Product id	Int
Quantity	Int
Created at	Datetime
Updated at	Datetime

Table 4: Structure of the suppliers

Field name	Data type
Id	Int
Supplier name	Varchar
Supplier location	Varchar
Email	Varchar
Created by	Int
Updated at	Datetime
Created at	Datetime

Table 5: Structure of the users

Field name	Data type
Id	Int
First name	Varchar
Last name	Varchar
Email	Varchar
Created at	Datetime
Updated at	Datetime

Table 6: Structure of the products purchasers

Field name	Data type
Id	Int
Supplier	Int
Product	Int
Created at	Datetime
Updated at	Datetime

The structures and other details of these tables can be altered according to the complexity and requirements of any given business concern. The present tables were made so simple for this paper.

Relationships or interconnections among the tables or the objects of the system for data manipulation and information retrieval are depicted in Fig. 5.

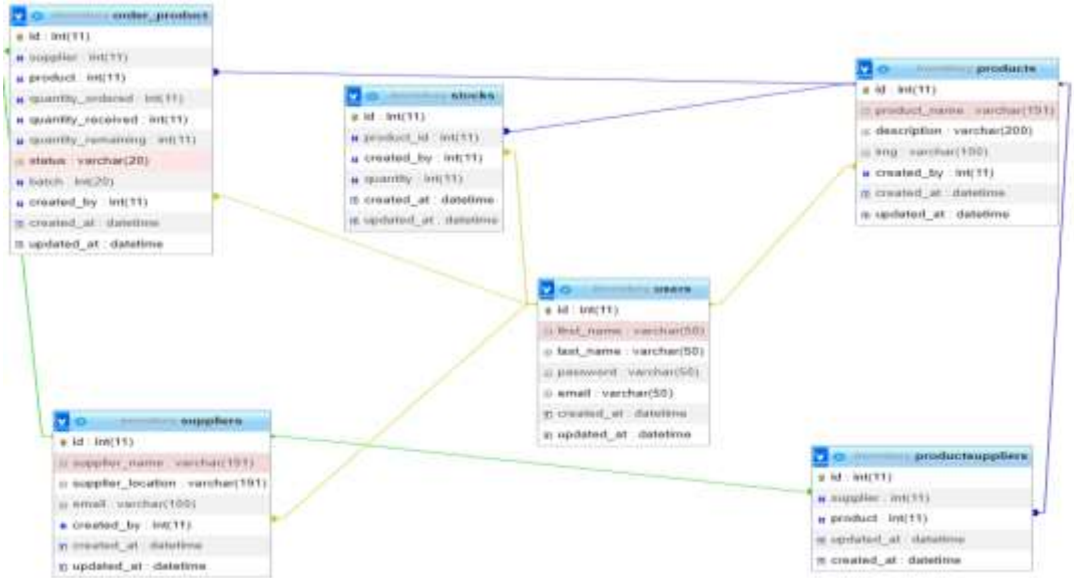

Figure 5: A Class Diagram

F. Design of the reports and receipts: The report entities are designed to present basic information required in the production cluster's receipt and reports. Such information can easily be extracted from the underlying tables through the query designed for the purpose.

The scope of the system is illustrated by the context diagram shown in Fig 6.

Figure 6: A Context Diagram of the System.

2.3.4.2 Non-Functional Requirements

The following are the non-functional requirements of the system considered during the development of the web-based inventory management system:

(a) Availability of the system
(b) User-friendliness of the system

(c) Maintainability of the system
(d) System Performance
(e) Security and Safety of the system

3. Results

3.1 ARMA (p,q) Models

The time series plot of the monthly quantity of production from July 2020 to December 2022 is shown in Fig. 7. The time series plot in Fig.7 does not exhibit any visible trends or seasonality. The need to ascertain whether the series is stationary or not was achieved using the Augmented Dickey-Fuller test.

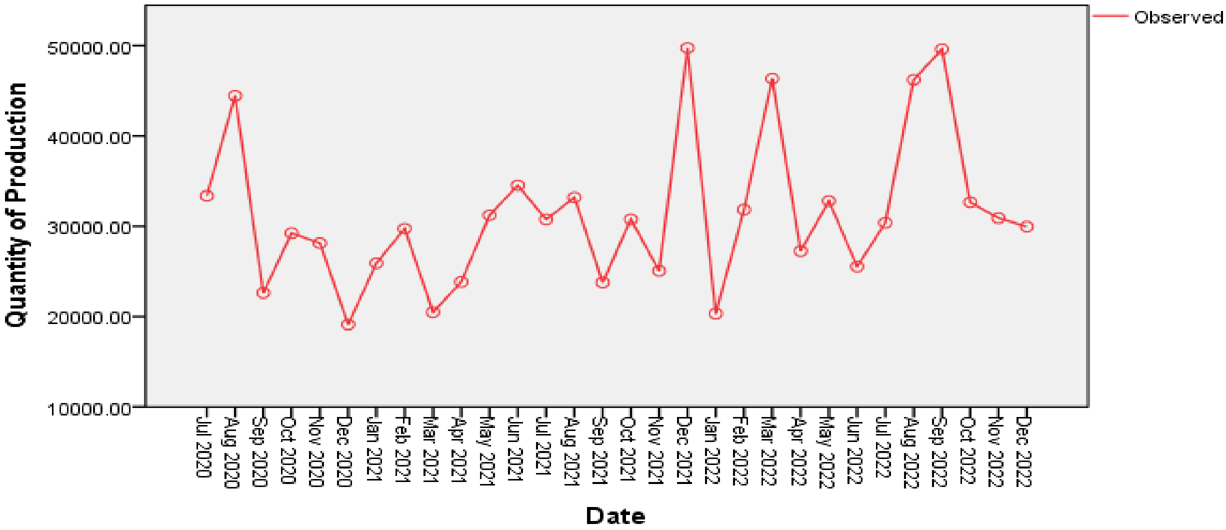

Figure 7: Time Series Plot of Monthly Quantity of Production

Table 7 shows the Augmented Dickey-Fuller test for the monthly quantity of production. The unit root test was carried using in R version 4.3.3 software. ADF test statistic obtained is -4.9096. The p-value for the monthly quantity of production is 0.01. The computed p-value is less than the significance alpha level ($\alpha = 0.05$), so the null hypothesis (H0) of a unit root in the time series is rejected. This result indicates that the time series is stationary and does not require differencing to achieve stationarity.

Table 7: Augmented Dickey-Fuller Test for Monthly Quantity of Production

Parameter	Value
ADF Statistic	-4.9096
p-value	0.01
Alpha	0.05
No. of Observation	30

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test was used to confirm the result obtained from the Dickey-Fuller test. In the KPSS, the null hypothesis for the test is that the data is stationary while the alternative hypothesis for the test is that the data is not stationary. Table 8 shows the KPSS test result for the time series. The test was carried at significance levels of 10, 5, 2.5, and 1%. The KPSS test statistic obtained is 0.3764. The critical values obtained at significance levels of 10, 5, 2.5, and 1% are 0.347, 0.463, 0.574, and 0.739 respectively. Since the KPSS statistic (0.3764) obtained is within the acceptance region of the hypothesis, the null hypothesis cannot be rejected. Hence, the KPSS test shows the monthly quantity of production in the unit stationary. This confirmed the earlier result obtained from the ADF test.

Table 8: KPSS Test for Monthly Quantity of Production Time Series

Parameter	Value
KPSS Test Statistic	0.3764
Critical value at significance level of 10%	0.347
Critical value at significance level of 5%	0.463
Critical value at significance level of 2.5%	0.574
Critical value at significance level of 1%	0.739

In this study, various ARMA (p,q) models were investigated; their parameters were estimated at a 95% confidence interval. The essence was to ensure that accurate orders of autoregressive (AR) and moving average (MA) were selected for forecasting of monthly quantity of production in the company. Here, t-statistic and p-value were used to determine the significant models. A significant model is a model whose all its parameters at a 95% confidence interval are all significant. Bayesian information criterion (BIC), mean absolute percentage error (MAPE), and root mean square error (RMSE) were the accuracy measures used in determining the best model from the tentatively significant ARMA models. The model with the lowest values of the listed accuracy measures was selected as the best ARMA model for the monthly quantity of production. Table 9 shows the summary of the examined ARMA models for forecasting of monthly quantity of production. From Table 9, only ARMA (1,1) is a significant model for the monthly quantity of production as can be seen from their t-statistic and p-values. Considering the accuracy measures, ARMA (1,1), which has the lowest BIC of 18.836, RMSE of 10987.903, and MAPE of 24.329, was selected for the monthly quantity of production.

Table 9: Summary of Parameter Estimation of ARMA Models for the Monthly Quantity of Production

Model	Parameter	Estimate	Standard Error	t-statistic	p-value	Bayesian Information Criterion	Root Mean Square Error	Mean Absolute Percentage Error
**ARMA(1,1)	AR 1	1.000	0.001	750.071	0.0001	18.836	10987.903	24.329
	MA 1	0.895	0.131	6.846	0.0001			
ARMA(2,1)	AR 1	0.963	0.233	4.133	0.0001	18.986	11191.330	24.325
	AR 2	0.036	0.232	0.157	0.876			
	MA 1	0.886	0.154	5.759	0.0001			
ARMA(3,1)	AR 1	0.974	0.219	4.451	0.0001	19.135	11394.329	24.623
	AR 2	-0.041	0.026	-1.585	0.125			
	AR 3	0.067	0.216	0.311	0.759			
	MA 1	0.868	0.192	4.520	0.0001			
ARMA(1,2)	AR 1	1.000	0.002	644.517	0.0001	18.986	11190.872	24.328
	MA 1	0.920	0.202	4.546	0.0001			
	MA 2	-0.030	0.209	-0.143	0.888			
ARIMA(1,3)	AR 1	0.999	0.002	447.663	0.0001	19.135	11390.986	25.168
	MA 1	0.933	0.206	4.521	0.0001			
	MA 2	0.078	0.266	0.295	0.770			
	MA 3	-0.161	0.218	-0.740	0.466			

**Significant model

The selected ARMA (1,1) model was subjected to diagnostic checking to ascertain its adequacy for forecasting of monthly quantity of production in the company. The diagnostic check to confirm the adequacy of the model showed that the model is adequate for forecasting the monthly production data in the company as can be seen in the plots of residuals ACF and PACF shown in Fig. 8. As can be seen from the figure, the ACF and the PACF of the residuals are not significant at any lag, meaning that serial correlation is not significant between the error terms. Hence, the model is significant. Table 10 shows the results of the overall adequacy of the model checked using the Ljung-Box statistic (Q* = 8.602 with degree of freedom = 16). The table confirmed that the model generated is adequate and a good fit for the monthly quantity of production data since the p-value ($p=0.929$) computed is greater than the alpha value ($\alpha=0.05$).

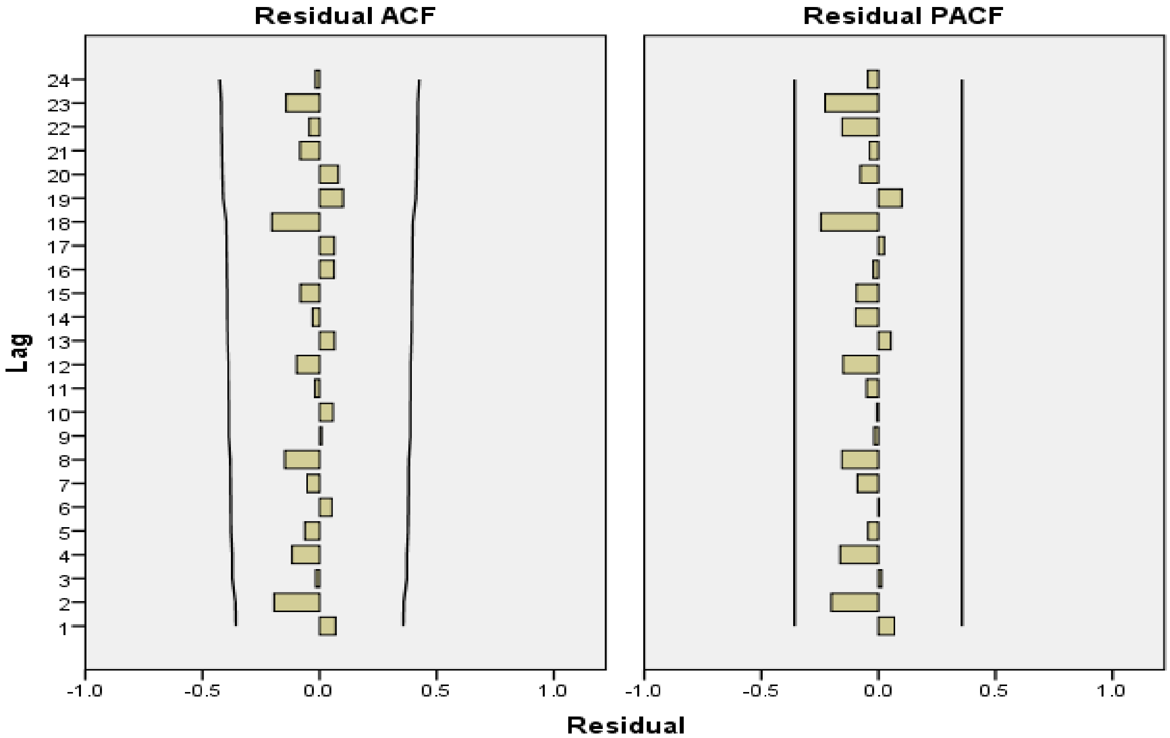

Figure 8: Residual ACF and PACF of the Monthly Quantity of Production

Table 10: Ljung-Box Q (18*) Statistic of the Monthly Quantity of Production

Model	Statistic	Degree of Freedom	p-value
ARIMA (1,1)	8.602	16	0.929

The essence of fitting an ARMA model is done to properly understand the system and be able to make forecasts based on the historical pattern of the time series. The statistically significant and adequate ARMA (1,1) model generated is mathematically represented as:

$$Y_t = \varphi_1 Y_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} \quad (6)$$

From Table 9, the value of AR (1) is 1.000 and that of MA (1) is 0.889, substituting the value in Eq. (6), the ARMA model for the monthly quantity of production in the company becomes;

$$Y_t = Y_{t-1} + \varepsilon_t + 0.889\varepsilon_{t-1} \quad (7)$$

Since the model was found to be adequate and good fit for the monthly quantity of production, the statistical significant and adequate ARMA (1,1) model generated was used to make 12 months forecast of monthly production in the company. Figure 9 shows the 12 months forecast made with the ARMA model. The red line shows the observed (actual), the thin blue line shows the fit, and the out of the sample thick blue line shows the forecast made.

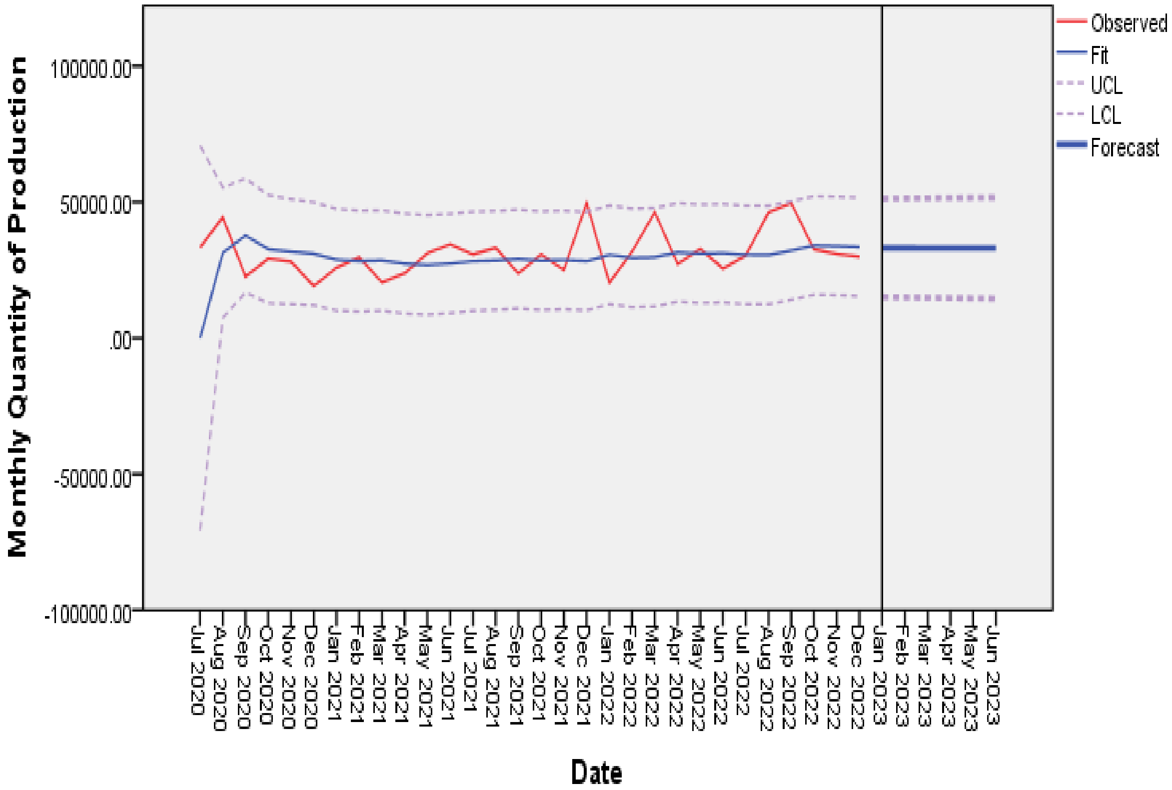

Figure 9: Residual ACF and PACF of the Monthly Quantity of Production

3.2 Web-based Inventory Management System

A web-based inventory management system for easy recording, visualization, and monitoring inventory in the Unizik plastic unit was developed using MySQL database as shown in Figs. 1 – 6. The database contains various useful information that has been invited into the inventory management system as can be seen in Tables 1 – 6. The ARMA model, economic order quantity, suppliers' details, customers, and other useful information were built into the system to enable continuous data collection, storage, and quick access to inventory data on the target establishment. If the user needs any information or data to conduct stock analytics, the user can always refer to the database of the inventory control system.

The system was tested using a combination of unit testing, integration testing, and user acceptance testing.

- ✓ *Unit testing:* Each module of the system was tested individually to ensure that it functioning correctly.
- ✓ *Integration testing:* The modules were tested together to ensure that they worked seamlessly.
- ✓ *User acceptance testing:* The system was tested by the business's staff to ensure that it met their requirements and was user-friendly.

4. Conclusion

A web-based inventory management system for easier recording and monitoring of raw materials, work-in-process, and finished goods inventories in Unizik plastic units and other small businesses was developed in this study using the MySQL database. The time series analysis of the monthly quantity of production in the unit using an autoregressive integrated moving average modeling approach was carried out. Out of the various ARMA models examined, ARMA (1,1) was selected as the most suitable model for the prediction of the monthly quantity of production based on the lowest BIC, RMSE, and MAPE values. The plots of residual ACF and PACF, and Ljung-Box statistics showed that the model generated is adequate and a good fit for the monthly quantity of production in the unit. The generated ARMA model, economic order quantity, suppliers, customers, and other useful information was built into the inventory management database developed for easier inventory control. With the web-based inventory control system application, the unit can make more informed decisions and plans for growth based on real-time data and predictions.

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