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Forecasting stochastic consumer portability visitation pattern in fair price shops of India

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Abstract

In India, the Public Distribution System (PDS) is a critical tool for accomplishing the aim of "Zero Hunger". Despite the enormous resources used, PDS has several inefficiencies that are caused by the monopoly of agents engaged in last-mile grain supply. Various state governments in India have been employing portability as an innovative solution to address this problem. In this article, we examined a huge-scale data on the deployment of portable beneficiaries arriving in a particular FPS of Kerala state in India over three years. A comparison is made between Auto-Regressive Integrated Moving Average (ARIMA) method which makes forecasts in univariate data and ARIMA with exogenous variables called ARIMAX. We followed Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD) as the accuracy performance measure of the models and observed that the ARIMAX model outperforms the ARIMA model with the least forecasting errors.

Subject Classification: *62M10, 91B84, 37M10.*

Keywords: *Auto-regressive integrated moving average (ARIMA), ARIMAX, Fair price shop (FPS), Mean absolute percentage error (MAPE), Mean absolute deviation (MAD), Public distribution system (PDS).*

1. Introduction

Geographical restrictions on mobility dictate where we can travel and what we can purchase, hence regulating human economic activity.

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Understanding consumer behavior is crucial for predicting market dynamics as well as for figuring out how previous performance predicts future performance at the micro level. We are more interested in anticipating where a person will travel next than we are in predicting how much money will be spent or what will be purchased. A key tool for accomplishing the aim of "Zero Hunger" in India is the Public Distribution System (PDS). About 800 million people receive basic food items like rice, wheat, and coarse grains under the PDS, a service developed by the central and state governments. Food grains are purchased at reduced prices by recipients at fair price shops (FPS) run by government-selected distributors. Despite significant budgetary commitments, the PDS is reportedly hampered by grain leakage to open markets, poor grain quality, and poor customer service [1, 20]. The existence of monopolistic agents in charge of the last-mile supply of food grains is a significant structural factor in these issues. These agents have high incentives to redirect subsidized grains to open markets but insufficient incentives to increase productivity and customer satisfaction [2, 3].

Portability is intended to be a technology driven solution that gives recipients choice reducing the monopolistic power that the retail dealers use. In India, PDS portability is primarily implemented at the intrastate level, allowing beneficiaries to receive their rations from any FPS located in their state of residence. By providing more stock, the traders of these FSPs became able to receive additional commissions. As their registered recipients switched to other FPSs, the volume of transactions at several FPSs in urban areas decreased. This was the situation of FPSs that were challenging to reach had limited space or had hygienic problems both within and outside the shop. It ultimately results in more stock being available at month's end and lower monthly commissions.

The challenges experienced by the dealers of the FPS are irregular monthly income and frequent experience losses, a decline in the beneficiaries' footfall as a result of their shop's location. Therefore it is important to investigate alternatives for making up for losses suffered by dealers as a result of portability and to perform a transaction data analysis to comprehend ration-taking trends and pay attention to the areas with unusually high or low transaction volumes. In the PDS, arguments for benefit portability frequently reference the difficulties faced by migrants. As a result, there is a huge disparity between supply and demand, and the FPS is paying more attention to the best way to manage commodities. This increases the importance and necessity of accurate estimates of future commodity demand and resource availability. Since this issue is stochastic, it must take into account beneficiaries' uncertain arrivals when they purchase commodities from the FPS when their RC is not mapped. Hence, there has been an increase in focus on the forecasting of beneficiaries' arrivals in FPS facilities, particularly the forecasting of migrants' visits which differs significantly from the forecasting of registered beneficiaries' visits. The distribution of the essential commodities for the FPS can be enhanced by accurate and reliable forecasts of the beneficiaries enrolled under various FPS (Portability rates). To assist the FPS dealers in successfully and timely meeting the anticipated commodities demand, it is important to develop an accurate forecast for the monthly portable beneficiaries count in advance.

In this article, we contribute to the discussion by analyzing large-scale data on the implementation of portable beneficiaries visiting in a specific FPS in the Kottayam district of Kerala state over three years. The remainder of the article is structured as follows: Section 2 reviews the existing literature. Section 3 discusses the methodology, the data set used, and the forecasting methods that are used to forecast portable beneficiaries. Section 4 presents the empirical findings and discussions. Conclusions are drawn in Section 5.

2. Literature Review

Earlier, each FPS dealer possessed a paper-based list of beneficiaries, and only after validating the beneficiaries' names on a government-issued RC would they distribute grains to beneficiaries. This system gave FPS dealers a monopoly over beneficiaries, which resulted in inefficient and subpar service, as seen by frequent FPS closures, abuse of beneficiaries, lengthy queues, impurity of grains, and overbilling or underweighting [5]. The end-to-end digitization of the PDS has been a goal of the central government and numerous states since 2010. The implementation of biometric authentication of beneficiaries through the installation of electronic devices at FPSs connected to central servers is a salient aspect of this effort [6]. One study discovered that beneficiaries prefer to utilize stores with superior service quality and road connectivity [17], whilst another observed that the proportion of beneficiaries using portability dropped to nearly zero within 18 months of the intervention's debut [18].

Supply chains in the modern age are connected to numerous sources of uncertainty and complications [19]. A dynamic demand and supply chain is influenced by a variety of factors, such as supplier behavior, consumption patterns, competitor behavior patterns, stochastic consumer visits, advancing technology, and the creation of new products [7]. The uncertainty in portability is a significant challenge in sales forecasting and demand prediction, making it difficult to resolve [8]. The demand forecasting and, thus, the quality of decision-making depends critically on accurate portability forecasting. Inaccurate forecasts could result in unnecessary expenditures for transportation, labor, inventory, and service levels [9]. Approaches to deal with the stochastic nature of consumer arrival and demand volatility have been presented and developed by researchers and practitioners. For instance, increasing inventory levels can help to mitigate the effects of demand fluctuation. This will assist in reducing demand volatility, but it comes at a high cost to the firms [10]. Increasing capacity is another method of reducing demand volatility, but it is not a very attractive choice because it is expensive for the supply chain.

The field of forecasting has extensively explored and is constantly developing time series methodologies [21]. ARIMA is one of the most extensively researched models in this field. ARIMA models may not be the ideal choice since complex time series data from the actual world is not necessarily linear. Various statistical models can be applied in situations like these to account for the non-linearity. The time series prediction approach is especially helpful when little is known about how an explanatory variable will affect the result. A dependent variable in a time series approach depends exclusively on its historical values. Once a model has been created, it is then applied to forecast future outcomes. For predicting retail sales over the last few decades, a variety of models have been employed [11]. Furthermore, no single strategy beats every other strategy in every situation and condition. But certain models may, however, perform more effectively than others in some situations. (Alon, Qi, and Sadowski, 2001), for instance, examined the forecasts produced by an Artificial Neural Network (ANN), Holt-Winters Method, ARIMA, and various combination techniques [12]. They found that while ANN and multiple aggregations may do well in volatile markets, ARIMA and triple exponential smoothing surpass the competition when macroeconomic factors are consistent. In demand forecasting, (Huang et al., 2014) analyzed the value of economic statistics such as pricing and marketing [13]. They began by identifying the most important explanatory factors before developing an autoregressive distributed lag model that produces favorable outcomes.

(Huang, Fildes, and Soopramanien, 2019) offered strategies for accounting for the conceptual shifts in demand brought on by advertising techniques [14]. These approaches either overestimate volatility as an element that can affect the forecasting quality of the model or do not consider it. Common forecasting methods called extrapolative approaches make the assumption that a series' historical behavior record is a good predictor of its future performance. As a result, we can forecast the series' future based on its association with other parameters [15]. (Hyndman, R., 2019) employed ARIMA and exponential smoothing techniques as two standard and effective analytical approaches. These techniques derive their predictions on extrapolations from historical patterns and rely on auto-correlations with historical data. Traditional time series models don't take into account the effect of influencing variables on demand and are unable to appropriately represent randomness in series [16]. Due to this, if the demand time series is volatile, a univariate ARIMA or exponential smoothing model may not perform well in its forecasting. To solve this issue, one can build ARIMAX and ETSX models and include influential variables in time-series data. Both autocorrelations and influencing variables are taken into account in these models, which offer potential new directions for time series literature.

3. The Methodology

3.1 *Data Description*

Monthly visits data of Portable beneficiaries in a specific FPS of Kottayam district in Kerala state of India over three years (January 2019 to December 2021) are used respectively. The state government of Kerala issues four different sorts of ration cards to its residents. They are Antyodaya Anna Yojana (AAY), Non-Priority Subsidy (NPS), Non-Priority Non-Subsidy (NPNS), and Priority House Hold (PHH). Kerala state issues AAY ration cards to the poorer people in the society. Individuals from the state who are not considered above the poverty line may apply for the NPS scheme sponsored by the Kerala government. People in the state who are below the poverty line will be issued ration cards under the PHH Scheme. The data span over a period of 36 months, starting in January 2019 till December 2021. The monthly visit data of Portable beneficiaries under each scheme is plotted in Figure 1.

3.2 *ARIMA and ARIMAX Model for Portability Forecasting*

George Box and Jenkins (1976) employed nearly the same technique for model description, which is replicated more transparently. The Autoregressive, Integration order, and Moving Average components

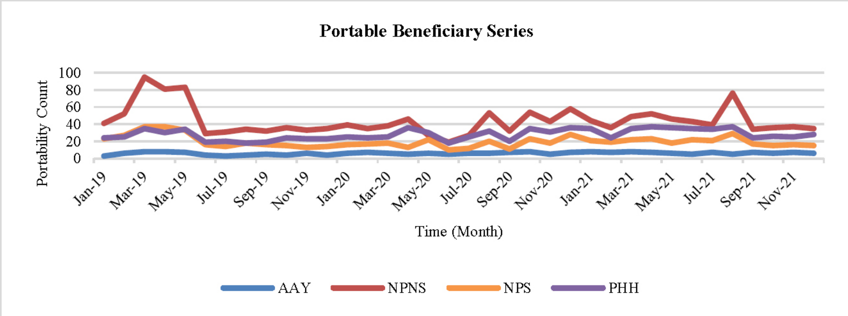

Figure 1

Monthly visits data of Portable beneficiaries under four schemes

make up the ARIMA (p, d, q) model processes. I(d), which refers to the integration's order is the first process that is required to be considered. To eliminate the unit root from a time-series data and make it stationary, integration order dictates the order of differencing. To construct a weakly stationary time series, which is the condition that the Box-Jenkins method most critically requires, we frequently have to modify the sequence even by natural log or square root to stabilize the variance [22]. The target variable's association with the linear combination (regression) of its previous values is defined by the AR(p) process, also known as the Autoregressive method of order p is given in Eq. (1).

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots\ldots\ldots\ldots + \phi_P y_{t-p} + \varepsilon t \tag{1}$$

The third process is the MA(q) referencing the moving average method of order "q", where the variable "yt" is a function of the present shock and several previous shocks (errors) calculation in given in Eq. (2).

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots\ldots\ldots\ldots + \theta_q \varepsilon_{t-q} \tag{2}$$

Where θ is the moving average coefficient and εt is white noise. Combining these three processes results in the ARIMA model, which is typically represented as ARIMA (p, d, q) is calculated using Eq. (3).

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots\ldots\ldots\ldots + \phi_P y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \tag{3}$$

The time series forecasting approach is especially beneficial when little is known about the impact of explanatory variables on outcomes. A dependent parameter or output in a time series model is only dependent on its previous values. After establishing a model, it is applied to forecast future values. When an explanatory variable is included, the ARIMA model can be upgraded to the ARIMAX model. A wide variety of models fall under the category of dynamic regressions, which uses the ARIMA model along with explanatory variables (ARIMAX). These models include popular multiple regression models, where input parameters directly influence the outcome values. Eqs. (4) and (5) are used to express the ARIMAX model as follows:

$$y_i = \beta x_i + \sum_{j=1}^{p} \phi_j (y_{i-j}) + \varepsilon_i + \sum_{j=}^{q} \theta_i \ (\varepsilon_{i-j}) \tag{4}$$

In lag operator form, it has the given compressed form:

$$\phi B y_t = C + \beta X_t + (B) \tag{5}$$

Where, *Xt* is an explanatory variable at time t. There can be multiple explanatory variables. In some cases, the influence of explanatory factors upon the dependent variable may be held by multiple lags in addition to the instantaneous impact. By taking the number of days in a month into account, which results in the ARIMAX model, the forecasting efficiency of the ARIMA model is enhanced. Because of the dynamic nature of the visiting pattern of portable customers into the FPS, there is an extremely significant link with the input variables chosen. Since the variables chosen as inputs have a significant impact on how well the ARIMAX model forecasts, the input variables must be selected in a manner that minimizes forecasting error. The monthly variation in the number of daily visit portable beneficiaries impacts the pattern of visits, making it a crucial component to take into account and incorporate into the presented ARIMAX model.

The current study makes an effort to carry out the two steps of the ARIMA and ARIMAX technique in portability forecasting by employing dynamic portable beneficiary data of an FPS in the Kerala State of India. It is crucial to create an accurate forecast for the monthly portable beneficiary count in advance to assist the FPS dealers to meet the anticipated commodities demand successfully and on schedule. Additionally, it aids in the effective planning of essential commodity requirements. The portability data indicate that portable beneficiaries arrive unexpectedly and outside of the control of the FPS and that the frequency of portable beneficiary visits exhibits significant cyclical, seasonal, and stochastic variations that are influenced by the weather, epidemic disease, the time of day, and social and demographic effects.

3.3 *Experimental / Empirical Results*

For portability forecasting, a statistical analysis of Kerala FPS portable beneficiary visiting patterns is performed. The two main computational procedures for developing a forecasting model for accurate portable forecasting are described below.

3.3.1 Choosing the order of the model

We must first evaluate the series for stationarity constraints before modeling with the ARIMA approach. For this, our paper employs the augmented-dickey-fuller test (ADF). The ADF test's null hypothesis (H0) implies that the data are non-stationary as they contain a unit root. The alternate hypothesis (*Ha*) implies data series is stationary as it does not contain a unit root. The ADF test implemented to the data series generated from all schemes reveals that the data is stationary, and hence it rejects the null hypothesis. So the order of differencing equals to ARIMA process's I(d) order is I(1) in our case. The ACF and PACF for the schemes AAY, NPS, NPSNS, and PHH determine the order of the AR and MA processes for the ARIMA and ARIMAX models, as shown in Figures 2. a, 2. b, 3. a, 3. b, 4. a, 4. b, 5. a and 5. b.

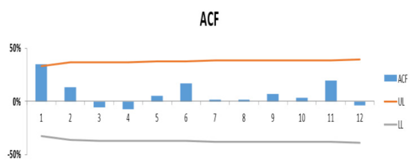

Figure 2.a

ACF Plot for AAY

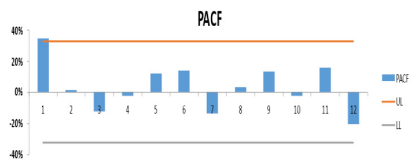

Figure 2.b

PACF Plot for AAY

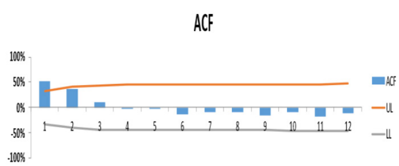

Figure 3.a

ACF Plot for NPS

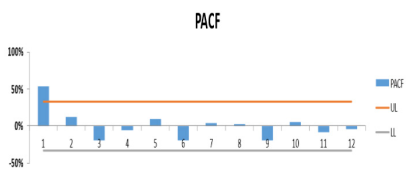

Figure 3.b

PACF Plot for NPS

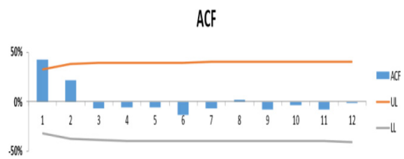

Figure 4.a

ACF Plot for NPNS

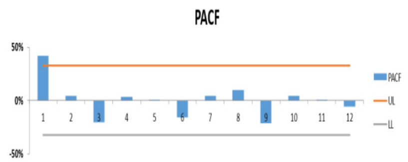

Figure 4.b

PACF Plot for NPNS

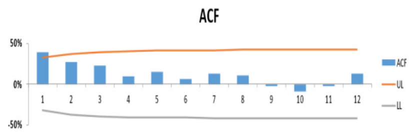

Figure 5.a

ACF Plot for PHH

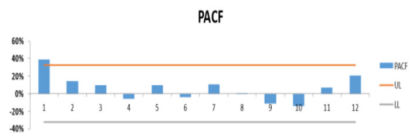

Figure 5.b

PACF Plot for PHH

Analysis of ACF and PACF plots is used to identify the ARIMA and ARIMAX model's initial order. The optimal ARIMA and ARIMAX model for each scheme was determined using the least Akaike Information Criterion (AIC) value. Table 1 below shows the optimal ARIMA and ARIMAX models for each scheme along with the lowest AIC value.

Table 1

Optimal ARIMA and ARIMAX Model with Lowest AIC Values

Scheme	Method	p	d	q	AIC
AAY	ARIMA	1	0	1	129.02
	ARIMAX	1	0	0	131.99
NPS	ARIMA	1	1	1	233.71
	ARIMAX	1	1	1	233.88
NPNS	ARIMA	1	0	1	304.79
	ARIMAX	1	0	1	303.60
PHH	ARIMA	1	0	1	233.29
	ARIMAX	1	0	1	228.96

3.3.2 Forecasting portability

The increase in the number of portable beneficiaries' visits to FPS is likely to occur every year so forecasting needs to be done in the future. The goal of forecasting is to make predictions using historical data and

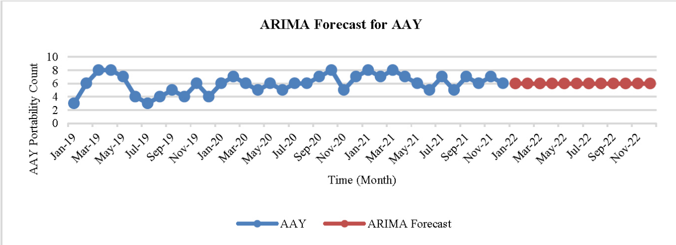

Figure 6

ARIMA Forecasting for AAY

relevant variables [23]. So forecasting is crucial for FPS since it may be used as guidelines when making vital plans and decisions. Finding patterns in historical data sets and extrapolating these trends into the future is the purpose of forecasting, which also aims to lower management risk and decision-making failures. The precise portable beneficiary arrival forecasts can act as a management baseline to better distribute commodities supply because overcrowding in FPS is a significant issue in many states. We employed the ARIMA and ARIMAX forecasting models to predict trends and create forecasts once we selected the most relevant model of portability in our instance. In our research, the portability data collected over 3 years from 2019 to 2021 is used to develop these models and is applied for forecasting the portable beneficiary for the next one year i.e for the year 2022. Figure 6 and 7 below shows the plot for the next one-year forecast of the portable beneficiary by fitting ARIMA(1,0,1) and ARIMAX (1,0,1) for AAY.

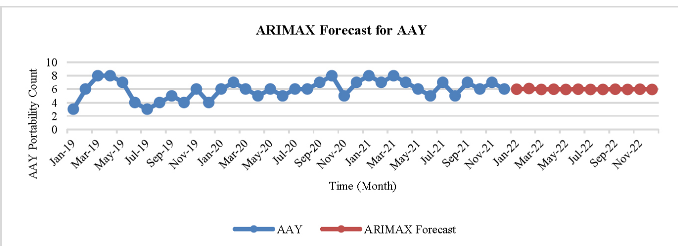

Figure 7

ARIMAX Forecasting for AAY

Figure 8 and 9 presents the results of the portable beneficiary forecasts for next one year by applying ARIMA(1,1,1) and ARIMAX(1,1,1) for NPS.

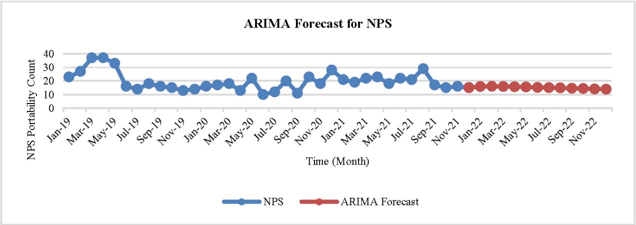

Figure 8

ARIMA Forecasting for NPS

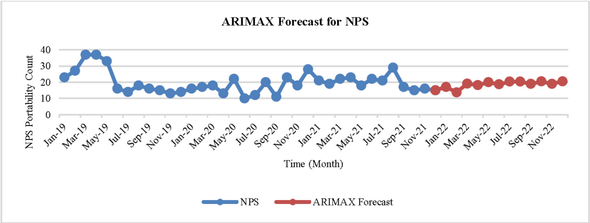

Figure 9

ARIMAX Forecasting for NPS

Figure 10 and 11 shows the results of the portable beneficiary forecasts for next one year by applying ARIMA (1, 0, 1) and ARIMAX (1, 0, 1) for NPNS

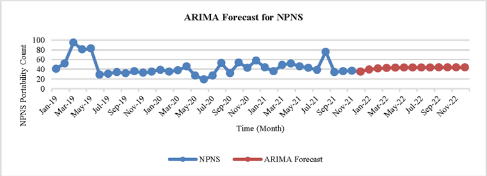

Figure 10

ARIMA Forecasting for NPNS

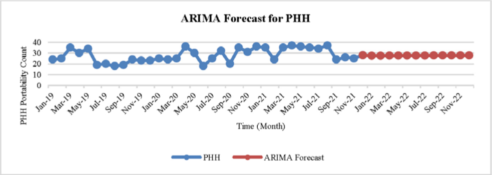

Figure 11

ARIMAX Forecasting for NPNS

Figure 12 and 13 presents the results of the portable beneficiary forecasts for next one year that we obtained by applying ARIMA(1,0,1) and ARIMAX(1,0,1) model for PHH to our time series data.

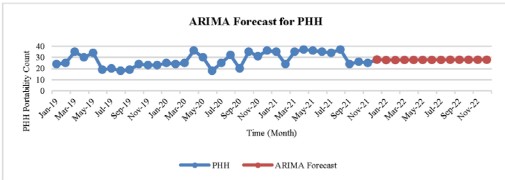

Figure 12

ARIMA forecast for PHH

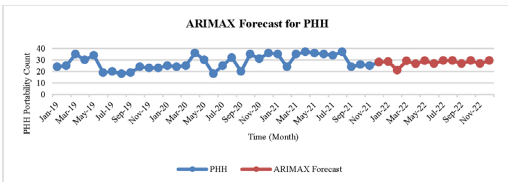

Figure 13

ARIMAX forecast for PHH

It is obvious that the models selected can be used to model and anticipate future portability data in the FPS of our study but each time we should enhance the previous data by adding additional information to improve the new concept and prediction. The estimates acquired through modeling helped in the choice to stock the commodities in this FPS. In fact, the model enabled us to anticipate demand and generate precise forecasts. Once we have the portability prediction, it will be easier and more obvious to make the appropriate inventory stock planning and so avoid huge cost losses. This will allow us to make better decisions about delivering raw materials and determining daily and future sales.

4. Results and Discussions

Time series analysis is a very useful tool to forecast the number of portable beneficiary visits required for planning inventory stock based on the portability visit whenever data of portable beneficiaries are recorded at regular intervals of time irrespective of the FPS where their RC is registered. ARIMA and ARIMAX models are essential and commonly used models because they provide a fundamental framework for modeling the impacts of data series dependency and allowing accurate statistical testing

(Velicer & Fava, 2003). To assess the accuracy of both models, it is essential to calculate the portable beneficiary forecast errors. In this investigation, we used Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD) as the model's accuracy performance metric. The MAPE is calculated using Eq. (6):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \times 100 \quad (6)$$

where $\hat{y}_i$ gives forecasting values and $\hat{y}_i$ represents observed values.

The MAD is calculated using Eq. (7):

$$MAD = \sum_{i=1}^{n}\frac{x_i - \bar{x}}{n} \quad (7)$$

Where x_i gives input values, $\bar{x}$ gives the mean for the specified collection of data and n gives the total count of metric values. Table 2 shows the comparison of ARIMA and ARIMAX models considering the smallest values of MAD and MAPE.

Table 2

ARIMA and ARIMAX Comparison with least MAD and MAPE Values

		ARIMA	ARIMAX
AAY	**MAD**	1.08554	1.07994
	MAPE	15.7158	15.6525
NPS	**MAD**	6.66579	3.59165
	MAPE	37.4789	19.1383
NPNS	**MAD**	8.77707	8.17561
	MAPE	19.8577	17.9513
PHH	**MAD**	5.46907	5.22548
	MAPE	16.5085	15.1751

As observed from the results of MAPE value, the multivariate ARIMA with explanatory variables outperforms the univariate ARIMA model with the least forecasting errors. The values of MAPE and MAD is lower in ARIMAX related to the ARIMA model in the 12-month forecast period. We recommend using the ARIMAX model over the ARIMA model whenever information on an exogenous variable is available, as more information leads to a better model. Figure 14 depicts the comparison of MAD for the ARIMA and ARIMAX model.

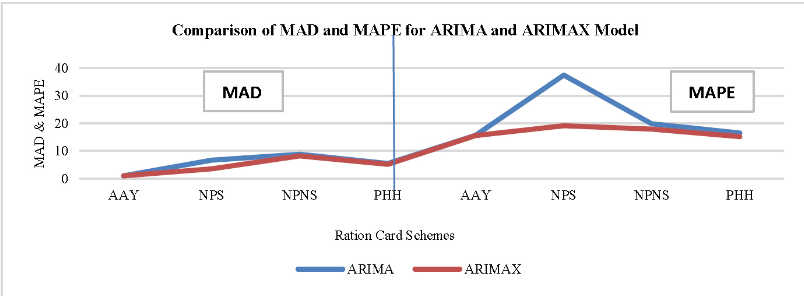

Figure 14

Comparison of MAD for ARIMA and ARIMAX model

5. Conclusion and Future Work

In this work, the widely used ARIMA and ARIMAX models for analyzing linear data trends were compared. With the ARIMAX model as its forecasting tool, the current study compares its results to those of the ARIMA model as a standard. The comparison was conducted using a particular FPS of Kerala state's monthly portability data set across a period of three years. It was observed that the most appropriate forecasting model for portability data is the ARIMAX model with lower MAPE for all four categories of ration card beneficiaries. ARIMAX model for all four categories based on their ration card group have the lower MAPE and MAD values can be considered better accurate models for forecasting portable beneficiaries in the FPS of Kerala taken for our study for the next year.

One of the limitation of our study is that we implemented the models only for one FPS. More FPSs in Kerala should be considered for this study to show the applicability of our models and to introduce a multi-method forecasting tool. More research is needed to look into additional factors that affect how often customers visit FPS in order to increase the models' accuracy. Future work will include additional investigations of beneficiary visitation patterns, as well as the integration of forecast models into an intelligent system that forecasts daily portability data visits. Future research would need to concentrate on improving the attribute selection strategy, examining its potential application to other domains, and discovering additional potentially important explanatory variables.

References

[1] Dreze, J., & Khera, R. Understanding Leakages in the Public Distribution System. Economic and Political Weekly, 50(7), 7-8 (2015).

[2] Pingali, P., Mittra, B., & Rahman, A. The bumpy road from food to nutrition security – Slow evolution of India's food policy. Global Food Security, 15, 77-84 (2017). https://doi.org/10.1016/j.gfs.2017.05.002.

[3] Banerjee, A., Hanna, R., Kyle, J., Olken, B. A., & Sumarto, S. Tangible Information and Citizen Empowerment: Identification Cards and Food Subsidy Programs in Indonesia. *Journal of Political Economy*, 126(2), 451-491 (2017). https://doi.org/10.1086/696226.

[4] Sharma, N., & Gupta, S. An investigation of IT-intervention adoption in public distribution system: A stakeholder and agency theory perspective. *Information Development*, 35(2), 203-219 (2017).

[5] Sargar, R., Kumar, A., Nakade, V., & Borkar, N. Public Distribution System in Solapur District of Maharashtra: A Case Study. International *Journal of Research in Engineering & Advanced Technology*, 2(3), 8 (2014).

[6] Allu, R., Deo, S., & Devalkar, S. Alternatives to Aadhaar-based Biometrics in the Public Distribution System. Economic & Political Weekly, 54(12), 30-37 (2019).

[7] Christopher, M., & Holweg, M. Supply chain 2.0 revisited: a framework for managing volatility-induced risk in the supply chain. *International Journal of Physical Distribution & Logistics Management*, 47(1), 2-17 (2017).

[8] Syntetos, A. A., Babai, Z., Boylan, J. E., Kolassa, S., & Nikolopoulos, K. Supply chain forecasting: Theory, practice, their gap and the future. *European Journal of Operational Research*, 252(1), 1-26 (2016).

[9] Torkul, O., Yılmaz, R., Selvi, I., & Cesur, M. R. A real-time inventory model to manage variance of demand for decreasing inventory holding cost. Computers & Industrial Engineering, 102, 435-439 (2016).

[10] Meindl, P., & Chopra, S. Supply chain management: Strategy, planning, and operation (2001). Prentice Hall.

[11] Aye, G. C., Balcilar, M., Gupta, R., & Majumdar, A. Forecasting aggregate retail sales: The case of South Africa. *International Journal of Production Economics*, 160, 66-79 (2015).

[12] Alon, I., Qi, M., & Sadowski, R. J. Forecasting aggregate retail sales: A comparison of artificial neural networks and traditional methods. *Journal of Retailing and Consumer Services*, 8(3), 147-156 (2001).

[13] Huang, T., Fildes, R., & Soopramanien, D. The value of competitive information in forecasting fmcg retail product sales and the variable selection problem. *European Journal of Operational Research*, 237(2), 738-748 (2014).

[14] Huang, T., Fildes, R., & Soopramanien, D. Forecasting retailer product sales in the presence of structural change. *European Journal of Operational Research* (2019).

[15] Makridakis, S., Spiliotis, E., & Assimakopoulos, V. The m4 competition: Results, findings, conclusion and way forward. *International Journal of Forecasting*, 34(4), 802-808 (2018).

[16] Huang, M.-G., Chang, P.-L., & Chou, Y.-C. Demand forecasting and smoothing capacity planning for products with high random demand volatility. *International Journal of Production Research*, 46(12), 3223-3239 (2008).

[17] Rajan, P., Chopra, S., Somasekhar, A. K., & Laux, C. Designing for food security: Portability and the expansion of user freedoms through the COREPDS in Chhattisgarh, India. Information Technologies & International Development (2016).

[18] Joshi, A., Sinha, D., & Patnaik, B. Credibility and Portability? : Lessons from CORE PDS Reforms in Chhattisgarh. Economic and Political Weekly, 51(37), 51-59 (2016).

[19] Sasi A, Subramanian T, Kumar Ravichandran S. Systematic Literature Review on Industry Revolution 4.0 to Enhance Supply Chain Operation Performance. In2022 5th International Conference on Computers in Management and Business (ICCMB), pp. 173-179 (2022 Jan 21).

[20] Ravichandran SK, Sasi A. Optimal Arrangement of Ration Items into Container Using Modified Forest Optimization Algorithm.

[21] Xie, N., Pearman, A.D. Forecasting energy consumption in China following instigation of an energy-saving policy. Nat Hazards 74, 639-659 (2014). https://doi.org/10.1007/s11069-014-1200-x.

[23] Archana Sasi & Thiruselvan Subramanian (2022) Comparative analysis of ARIMA and double exponential smoothing for forecasting rice sales in fair price shop, *Journal of Statistics and Management Systems*, 25:7, 1601-1619, DOI: 10.1080/09720510.2022.2130572.

[24] YaLi Yuan. Forecasting method for import and export trade on the basis of GMDH network model, *Journal of Discrete Mathematical Sciences and Cryptography*, 20:4, 755-766 (2017), DOI: 10.1080/09720529.2017.1358859.