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Market size growth survival in multi-generation technology environment: A predictive review of the Indian air-conditioner and refrigerator industry

Ayan Chattopadhyay [a]
Somarata Chakraborty [b]

[a] Associate Professor; Army Institute of Management Kolkata, Judges Court Road, Alipore, Kolkata-700027 Maulana Abul Kalam Azad University of Technology, India

[b] Assistant Professor; Army Institute of Management Kolkata, Judges Court Road, Alipore, Kolkata-700027, Maulana Abul Kalam Azad University of Technology, India

✉ *chattopadhyay.ayan28@gmail.com (Corresponding author)*

Corresponding author

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ABSTRACT

The ensuing paper aims to explore the future growth pattern of the market size of air-conditioner and refrigerator industry in India. Though this industry has witnessed phenomenal growth in the past, with multi-generation technology products driving it, its growth has remained erratic in nature. This paper also ratifies if the industry would survive the existing market size growth trend. In this predictive assessment, univariate time series data of net sales, collected from CMIE, is used. The data, spreading across 14 years, have 56 observations and exhibit both trend and seasonality. Forecast of market size is made using the best model derived from comparative approaches that include SARIMA, triple exponential smoothing and neural network. SARIMA model is found to best fit the historical data for predictive purpose and the study outcome suggests market size to grow till 2020. Finally, Weibull's function is used to analyze reliability of the forecast results which indicates diminishing trend of the market size growth. Finally, it is concluded that the current erratic nature of market size growth would disappear.

Contribution/ Originality

The market size forecast of Indian air-conditioner and refrigerator industry have been made by institutions, but individually. In this sense, this paper is novel. Further, reliability estimation of market size growth for this industry have not been found which makes it distinct among existing contributions.

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1. INTRODUCTION

The Domestic Appliance Industry (DAI) is growing big in India. Centre for Monitoring Indian Economy (CMIE) has further classified this industry into three sub-industries; Air-Conditioner and Refrigerator (AC&Ref), Consumer Electronics (CE) and Other Domestic Appliances (ODA) industry. While AC&Ref industry comprises of room air-conditioners (both window and split AC), the CE industry include products like conventional TVs, flat panel TVs, camera, sound systems etc., and micro wave ovens, washing machines, small domestic appliances, water purifiers etc. constitute the ODA industry. The industry net sales i.e. gross sales less sales returns and other applicable discounts represent the industry size which is also termed as market size. A close look into the industry figures reveal that the DAI in India has posted a staggering growth of 310% from 15.15 Billion USD to 62.18 Billion USD between 2004 and 2017 (CMIE, 2018). Furthermore, all the three sub-industries within the DAI have been found to grow in terms of market size during the same time period. However, two conspicuous patterns in the AC&Ref industry grabbed the attention of the researchers; first, is the behaviour of industry share (IS) and second, changes in the year on year Market Size Growth (MSG). The Compounded Annual Growth Rate (CAGR) of the market size for AC&Ref, CE & ODA industries (Table 1), indicates that AC&Ref industry has outperformed the other two industries.

Table 1: CAGR of domestic appliance industry market sizes in India (percentage)

Time Period		AC&Ref	CE	ODA	DAI
Last 14 Yrs	(2004-2017)	18.6	4.5	12.2	10.6
Last 10 Yrs	(2008-2017)	24.0	0.9	13.7	10.3
Last 5 Yrs	(2013-2017)	29.2	-3.3	7.0	9.2

Source: Authors computations based on CMIE (2018) data

Table 2 captures the MSG and IS of domestic appliance industries in India from 2004 till 2017. The change in IS of AC&Ref industry is distinctly different from that of both CE and ODA industries. AC&Ref IS grew from 17% to 45% between 2004 and 2017 while CE IS slipped from 60% to 27% during the same time period; however ODA industry share remained steady around its mean of 24% (CMIE, 2018). The uniqueness of AC&Ref industry is also evident with regards to the MSG behaviour. Except in the year 2005, the AC&Ref industry has posted a positive MSG till 2017 while CE and ODA industries have shown random fluctuations.

Table 2: MSG (Y-o-Y) and IS of domestic appliance industries in India (percentage)

Year	Air Conditioner & Refrigerator		Consumer Electronics		Other Domestic Appliances		Total Domestic Appliances	
	Market Size Growth	Industry Share	Market Size Growth	Industry Share	Market Size Growth	Industry Share	Market Size Growth	Industry Share
2004		17		60.1		22.8		100
2005	-19	14.1	-3	59.1	16	26.8	-2	100
2006	21	12.7	54	67.6	-1	19.7	35	100
2007	24	13.5	7	62.0	45	24.5	16	100
2008	4	13.9	6	65.6	-16	20.4	0	100
2009	20	14.9	4	61.0	32	24.1	12	100
2010	53	19.5	23	63.8	-19	16.7	17	100
2011	7	20.3	5	64.7	-7	15.1	3	100
2012	10	19.9	-5	54.5	91	25.7	12	100
2013	9	19.4	2	49.8	34	30.7	12	100
2014	59	26.9	7	46.5	-1	26.5	15	100
2015	25	30.9	-1	42.3	10	26.7	9	100
2016	46	39.7	-22	28.8	34	31.4	14%	100

2017	24	45.1	3	27.1	-4	27.8	9%	100

Source: Authors computations based on CMIE (2018) data

The MSG of domestic appliance industry is found to depend heavily on the AC&Ref industry. With about 45% contribution (as at 2017 year-end) that has grown steadily in the last 5 years, the importance of AC&Ref industry in the overall business of DAI is undeniable. Such figures undoubtedly indicate massive expansion of AC&Ref industry and an immense opportunity for future business is also foreseen as the product penetration levels of both air-conditioners (AC) and refrigerators (REF) in India are pretty low. Motilal Oswal (2018) reports 10% of Indian urban households to have air-conditioners while refrigerators have 37% penetration. Ernst and Young (2017) highlights rapid urbanization, rising disposable income, product innovation and lower product penetration as the key drivers of domestic appliance industry growth. Very low penetration of air-conditioners and low refrigerator penetration has certainly fuelled the MSG of AC&Ref industry, however, the researchers further opine that such growths may have been brought about by two more phenomena. The first one is that of increasing penetration of household electricity in India; especially in regions beyond the urban India, since both AC and refrigerator functions in an uninterrupted power supply condition. The second one is the sustained multi-generation product innovation. Both these industries are highly technology driven and this industry has witnessed launch of successive generation of products with additional functionality to the existing ones. Multi-generation products are aimed at improving product quality, quicker returns on investment and managing market uncertainties (Anand *et al.*, 2016). Nonetheless, such new innovations in the market place do not replace the previous ones that it intends to substitute immediately, however, it starts to compete with it and a series of parallel diffusions takes place in the market (Kapur *et al.*, 2015). Also, new generation innovation tends to cannibalize the sale of existing generation in the market (Mahajan and Muller, 1979) and identifying the exact impact of substitution or cannibalization of a new technology is extremely difficult. The researchers did not find adequate literature on multi-generation technological innovation for both air-conditioners and refrigerators in Indian context. To gain insights on the same, primary survey was conducted in the form of panel opinion with 4 experts from different organizations. Each panel member had more than 20 years of continuous experience in related industries and consensus of panel is depicted in Table 3.

Table 3: Multi-generation technology innovation of air-conditioners and refrigerators in India

Air-Conditioner		Refrigerator	
Period	**Major Technology**	**Period**	**Major Technology**
Pre 2002	Window	Pre 1992	Direct Cool
2002-03	Split	1992	Frost Free
2004-05	Hot & Cold	2006-07	DIOS
2005-06	Multi-flow Condenser	2007-08	PCB
2011-12	Inverter	2013-14	Inverter Linear Compressor & Dual Mode
2013-14	Dual Compressor	2014-15	Smart Diagnostics
		2016	Internet Controlled Smart Refrigerators

Source: Author's findings from primary survey of AC&Ref industry experts

While all of the above mentioned factors have driven the AC&Ref industry for a long 14 years, gradual market saturation effect, initiating from the urban areas, is a natural outcome that cannot be ignored (Hall and Khan, 2003). Thus, urban markets which have experienced higher product penetration are likely to become saturated first, and their future market size growth would depend upon the behaviour of (i) replacement (substitution) market and (ii) balance first time buyers. New business from the replacement market would heavily rest on the rate at which continuous multi-generation product innovation would diffuse through the social system leading to new product adoption. Rogers (1983) highlights that industries governed by an increasing level of saturation and those which also rely largely upon the replacement market would be typically characterized by higher advertising expenditure in mass media. It is done with an aim to ensure rapid and efficient means of informing potential adopters about innovation. The same trend is visible in AC&Ref industry as well. The

Advertising to Net Sales Ratio (ANSR) in 2005 was as high as 4.5% (CMIE, 2018), indicating difficulty in diffusion and adoption of these products. Subsequently, as adoption rate (market size) increased, ANSR slipped continually and touched 1.1% in 2014 (CMIE, 2018). Again this ratio is on an upward swing and has scaled to 1.9% in 2017 (CMIE, 2018), which may be construed as an indicator of concerns related to diffusion and adoption of products. On the other hand, un-penetrated markets in urban markets (balance first time buyers), semi-urban and rural India are expected to maintain the industry size growth momentum as majority of the first time buying is yet to happen and saturation effect will take its time to set in. In fact in the long run these markets are poised to become the mainstay for industry growth and its survival. However, both air-conditioners and refrigerators being 'high-involvement' products, the first time sales in these markets are not as easy as it seems from the low penetration figures. It must also be noted that the balance first time urban buyers are definitely slow adopters. Probably that is a prime reason why companies maintain a high focus on the replacement markets as well. Semi-urban and rural markets in India have their own challenges, especially with respect to the available power supply load against that required to run these products, education, income levels and the extent of lifestyle changes.

The outcome of these concurrently transpiring complex market effects remain unknown and so are the prospects of the overall industry. Such scenario triggered the quest for a primary objective-oriented inquiry into the future market size of the prime stakeholder of the domestic appliance industry, i.e. AC&Ref industry, in India. The second objective framed explores whether the AC&Ref industry market size would continue to grow and if the MSG pattern would survive, as seen in the last five years, while the last objective aims to evaluate reliability of the predicted MSG. Keeping in mind these objectives, the researchers have put in efforts to predict the future of AC&Ref industry by developing alternative forecasting models. Two statistical forecasting approaches; the Seasonal ARIMA (SARIMA) and Triple Exponential Smoothing (TES); have been considered. Also, Neural Network Auto Regression (NNAR), a machine learning method is deployed and a comparison made among them. Selection of the best forecasting model is guided by Mean Absolute Percentage Error (MAPE), an accuracy parameter. The best selected model is finally used to make forecast of the market size and its growth pattern till 2020. The rest of the paper is organized as follows. Section 2 provides an overview of the forecasting approaches used. Section 3 provides details of the empirical evaluation including those of model selection, forecasting and reliability measurement. Finally in section 4 conclusions have been drawn.

2. REVIEW OF TIME SERIES FORECASTING APPROACHES & RELIABILITY ESTIMATION

Among the extensively used forecasting techniques in business are the exponential smoothing methods (Bermudez *et al.*, 2007) which includes Single, Double and Triple Exponential Smoothing Techniques and the Box-Jenkins ARIMA Models (Maria and Eva, 2011). The latter is one of the most powerful forecasting techniques available owing to its capability of analyzing practically every univariate data set (Christodoulos *et al.*, 2010). It is expressed through the development of an ARIMA model and its seasonal variant, SARIMA, which are generalizations of ARMA model (Newbold, 1983). It is learned from literature that ARIMA has been applied in sales forecasting over the years across diverse industries; including those of automobile sales prediction (Sana *et al.*, 2017), order and retail sales forecasts of consumer durables (Mircetic *et al.*, 2016), demand in a beverage supply chain using SARIMA (Hanssens, 1998), sales forecast (Yucesan, 2018), oil sales forecasting (AlfAki *et al.*, 2015), consumer goods demand forecast (Dhini *et al.*, 2015), market potential (Waheeduzzaman, 2008) to cite a few. Past researches also advocate machine learning (ML), especially neural networks (NN), as a prominent alternative to the statistical approaches of time series forecasting (Qi and Zhang, 2008). NN is based on the principles of non-linear algorithm of error minimization as opposed to the linear approach adopted in statistical methods (Makridakis *et al.*, 2018). Comparative approaches have been deployed in this study to select the best model i.e. model with minimum error and market size forecast made with it. In the subsequent sub-sections, the theoretical basis of ARIMA, SARIMA, triple exponential smoothing (TES) and NN approaches have been presented. Finally, Weibull's distribution for reliability estimation has been discussed.

2.1. The ARIMA & SARIMA models

The ARIMA method offers a comprehensive aid to univariate time series model selection with a significant level of flexibility. Both ARIMA and SARIMA uses an iterative model building strategy which consists of three steps, namely; model identification, model estimation and model checking.

2.1.1. Model identification

It includes checking stationarity in data series using Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979). Differencing is done until stationarity is achieved. Furthermore, model identification is done on the basis of Akaike Information Criteria (AIC) (Akaike, 1974), Bayesian Information Criteria (BIC) (Schwarz, 1978) and principle of parsimony.

2.1.2. Model estimation

It is carried out on all the preliminary identified models to ensure co-efficients have t-statistic ≥ 2 (Cooper and Hedges, 1994) and have minimum error statistics for which mean absolute percentage error (MAPE) has been used. The prediction capability levels of MAPE is followed from Lewis (1982) and is shown in Table 4.

Table 4: Prediction capability levels of MAPE

MAPE (%)	Prediction Capability
< 10	Highly accurate
10–20	Good
20–50	Reasonable
> 50	Inaccurate

Source: Adapted from Lewis (1982)

2.1.3. Model checking

The best fitted model is selected on the basis of tests of residuals. It includes Ljung-Box test (Ljung and Box, 1978; Hanke and Wichern, 2015) for checking presence of serial correlation, auto regressive conditional heteroscedasticity (ARCH) test (Engle, 1982) for inspecting homoscedasticity and Jarque-Bera test (Jarque and Bera, 1980) for examining normality.

2.2. Triple exponential smoothing

When the time series shows seasonal pattern, Winter's three parameter linear and seasonal exponential smoothing; also known as Holt-Winters or Triple exponential smoothing technique (Winters, 1960), best handles the data series to reduce forecast errors. The seasonal component in TES can either be additive or multiplicative. Four components used to describe TES (Hanke and Wichern, 2015) are: (1) Exponentially Smoothed series (level estimate), (2) The trend estimate, (3) The seasonality estimate, and (4) The forecast for *p*-periods into the future.

2.3. Neural network auto regression

Artificial neural networks (ANN) are simple structural replications that attempt to imitate the behaviour of human brains. It allows complex nonlinear relationships between the response variable and its predictors. In the case of a multi-layered feed forward network (Figure 1), the inputs to each node are formed using a weighted linear combination and results transformed using a non-linear function before generating the output. According to Hyndman and Athanasopoulos (2014), the inputs to a hidden neuron j is linearly combined as $z_j = b_j + \sum_{i=1}^{n} w_{i,j} x_i$ where z_j: input to the hidden neuron, b_j: a parameter and $w_{i,j}$: weights of i^{th} input to neuron j and n: number of inputs. In the hidden layer, transformation is made using an activation function like sigmoid. This concept applies to time series forecasting as well where the lagged values act as inputs to a neural network, and the model is referred to as neural network auto regression (NNAR). It follows the notation NNAR (p,k) where p:

lagged inputs and k: number of hidden layers. In case of seasonality in data, the last observations from the same season are also added as inputs to the model. It is represented as NNAR(p,P,k)$_m$ with $y_{t-1}, y_{t-2}, \dots, y_{t-p}, y_{t-m}, y_{t-2m}, y_{t-Pm}$ as the inputs, m: seasonality and P: seasonal counterpart of p. k is calculated as $(1+p+P)/_2$ and is rounded off to the nearest integer incase k is not specified.

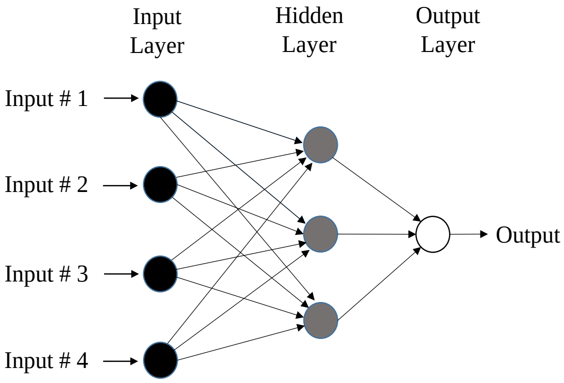

Figure 1: Non-Linear NN model with one hidden layer

Source: Adapted from Hyndman and Athanasopoulos (2014)

2.4. Reliability estimation modelling

Reliability forms an important property not only for systems but also for social phenomenon. Its quantification has gained prime focus owing to its ability to identify potential threats and estimate risks. Immense application of reliability measurement involving life data is noticed. Also, an increasing use of non-life data is found across diverse disciplines. Literature suggests several probability distributions for reckoning reliability; the most commonly used ones being exponential, lognormal, gamma and Weibull functions with 1, 2 and 3 parameters. Of all these, the latter and its analogue (for non-life data) are vastly popular owing to its flexibility (Ahmad *et al.*, 2009). The reliability of a 2 parameter Weibull distribution is given $R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}}$. Here, t: survival time i.e. time for a system to fail; β: shape parameter which is the slope of the curve and η: scale parameter that represents the spread of the distribution.

Use of non-life data in Weibull distribution can be found in reliability estimation of different types of capacity analysis, including freeway traffic capacity (Brilon *et al.*, 2005; Wu, 2013), travel time prediction (Dong and Mahmasani, 2009a/b), flow breakdown estimation (Elefteriadou *et al.*, 2009), customer satisfaction (Hadiyat *et al.*, 2017) to name a few. These studies have used a distribution analogous to that of Weibull's reliability function and replaced life data with non-life statistics. Focusing on the present study, market size growth (MSG) indicates the maximum capacity by which market size has grown and when measured against a threshold level, its acceptability can be ascertained. As a phenomenon, market size growth can be regarded as a failure if it is below the threshold level which has been considered as the geometric mean of the observed market size growth in the past 10 years. Table 5 shows the analogy between MSG capacity analysis and lifetime data analysis which forms the basis of reliability estimation in this study.

The MSG data is first checked with regard to its usage as an analogue to lifetime data in Weibull distribution (Brilon *et al.*, 2005). Results are found to be satisfactory as MSG exhibits randomness and its shape parameter is fairly constant across sample datasets.

Table 5: Analogy between lifetime data analysis and market size growth (MSG) capacity analysis

	Lifetime data Analysis	MSG Capacity Analysis
Parameter	Time, t	MSG, q
Failure Event	Death at time, t	Breakdown at MSG benchmark, q
Lifetime Variable	Lifetime, T	MSG Capacity, c
Survival Function	$S(t) = 1 – F(t)$	$S_c(q) = 1 – F_c(q)$
Probability Density Function	$f(t)$	$F_c(q)$
Probability Distribution Function	$F(t)$	$F_c(q)$

Source: Adapted from Brilon *et al.* (2005)

3. EMPIRICAL ANALYSIS

3.1. Data collection and treatment

The present study makes a forecast of market size of AC&Ref industry using comparative approaches. Secondary data used in this study was collected from Centre for Monitoring Indian Economy (CMIE). Quarterly net sales data of Indian domestic appliance industry and its sub-groups were available from 2004 till 2017 at the time of data collection; which means an availability of 56 observations (Figure 2). It is learned that for a fairly accurate estimation using suitable ARIMA methods, a minimum of 28 observations helps (Hanke and Wichern, 2015). Presence of outliers in many real data sets being a common phenomenon, test was conducted to identify them and also obtain their replacement estimates. 4 outliers were detected and were suitably substituted. Finally, for the purpose of model building using appropriate ARIMA technique, the data was split into training (75% i.e. 42 observations) and testing (25% i.e. 14 samples) sets as per usual practice and model developed from the former. Such models have been compared with those generated from an appropriate exponential smoothing method and the neural network approach.

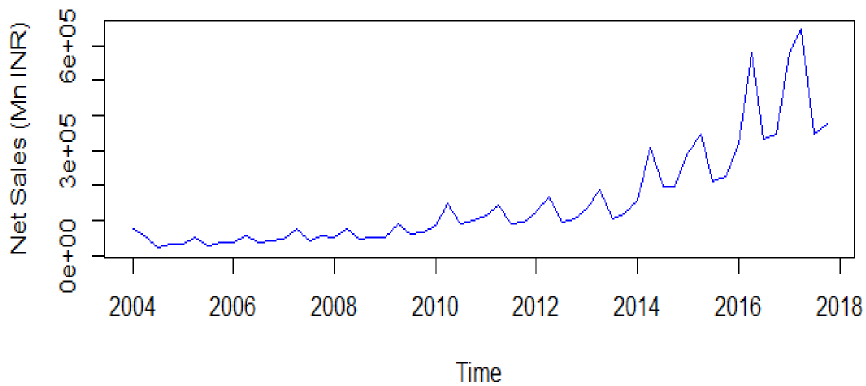

Figure 2: Quarterly net sales of AC&REF (2004-2017)

Source: Authors computations using data adapted from CMIE (2018)

3.2. Findings and analysis of SARIMA modelling approaches

The researchers begin their analysis with the original non-transformed data series (units series) by conducting tests for detecting trend, seasonality and stationarity. Table 6 captures the output of these tests and it was concluded presence of trend, seasonality and stationarity in the data set.

Table 6: Analysis of units series of AC&REF

Type of Test	Name of Test	Output	Remarks
Trend Analysis (Units Series)	Mann-Kendall trend test	*p*-value = 2.2e-16	Trend present
Seasonality Analysis (Units Series)	ETS	ETS (M,A,M)	Seasonality present
Stationarity Test (Units Series)	Augmented Dickey-Fuller Test	*p*-value = 0.01	Stationary data

Source: Authors own computations

The best possible models have been generated using the "forecast" package of R software with Kwaitkowski-Philips-Schmidt-Shin test (KPSS) specified for trend-stationarity. The method for selecting the best-fitted model is based on the minimum values of AIC (Akaike Information Criterion) and BIC. ARIMA(0,1,1)(1,1,0)[4] chosen by AIC is thus considered as the best fitted model. Table 7 shows the comparative models chosen by AIC and BIC. The outputs suggest that by default, differencing to order 1 has been executed. To test stationarity of the data series (d=1), test was conducted. p-value of ADF Test < 0.05 confirmed stationarity in the differenced dataset.

Table 7: Suggested ARIMA models based on AIC & BIC (Units Series)

ARIMA MODELS	AIC	ARIMA MODELS	BIC
ARIMA(2,1,2)(1,1,1)[4]	Inf	ARIMA(2,1,2)(1,1,1)[4]	Inf
ARIMA(0,1,0)(0,1,0)[4]	932.5316	ARIMA(0,1,0)(0,1,0)[4]	934.3817
ARIMA(1,1,0)(1,1,0)[4]	923.6781	ARIMA(1,1,0)(1,1,0)[4]	929.2285
ARIMA(0,1,1)(0,1,1)[4]	924.7294	ARIMA(0,1,1)(0,1,1)[4]	930.2799
ARIMA(1,1,0)(0,1,0)[4]	928.961	ARIMA(1,1,0)(0,1,0)[4]	932.6613
ARIMA(1,1,0)(2,1,0)[4]	Inf	ARIMA(1,1,0)(2,1,0)[4]	Inf
ARIMA(1,1,0)(1,1,1)[4]	Inf	ARIMA(1,1,0)(1,1,1)[4]	Inf
ARIMA(1,1,0)(2,1,1)[4]	Inf	ARIMA(1,1,0)(2,1,1)[4]	Inf
ARIMA(0,1,0)(1,1,0)[4]	925.0177	ARIMA(0,1,0)(1,1,0)[4]	928.718
ARIMA(2,1,0)(1,1,0)[4]	Inf	ARIMA(0,1,1)(1,1,0)[4]	924.1356
ARIMA(1,1,1)(1,1,0)[4]	920.5831	ARIMA(1,1,2)(1,1,0)[4]	928.1688
ARIMA(2,1,2)(1,1,0)[4]	Inf	ARIMA(0,1,1)(0,1,0)[4]	929.9528
ARIMA(1,1,1)(0,1,0)[4]	928.2511	ARIMA(0,1,1)(2,1,0)[4]	Inf
ARIMA(1,1,1)(2,1,0)[4]	Inf	ARIMA(0,1,1)(1,1,1)[4]	Inf
ARIMA(1,1,1)(1,1,1)[4]	Inf	ARIMA(0,1,1)(2,1,1)[4]	Inf
ARIMA(1,1,1)(2,1,1)[4]	Inf	ARIMA(1,1,1)(1,1,0)[4]	927.9837
ARIMA(0,1,1)(1,1,0)[4]	918.5852	ARIMA(0,1,2)(1,1,0)[4]	Inf
ARIMA(0,1,2)(1,1,0)[4]	Inf		
ARIMA(1,1,2)(1,1,0)[4]	918.9181		
ARIMA(0,1,1)(0,1,0)[4]	926.2525		
ARIMA(0,1,1)(2,1,0)[4]	Inf		
ARIMA(0,1,1)(1,1,1)[4]	Inf		
ARIMA(0,1,1)(2,1,1)[4]	Inf		
Best model ARIMA(0,1,1)(1,1,0)[4]		Best model ARIMA(0,1,1)(1,1,0)[4]	

Source: Authors own computations

The estimates of the best fitted model chosen by AIC i.e. ARIMA(0,1,1)(1,1,0)[4] was then found out (Table 8). It is observed that both ma1 and sar1 are significant as t-statistic > 2 (Cooper and Hedges, 1994) with a MAPE of 10% which is fairly good and accurate according to Lewis (1982).

Table 8: Summary of best fitted units series ARIMA Model (AC&REF)

Model	AIC	BIC	Coefficients			t-Statistic	Sig.	MAPE	~~MAE~~
ARIMA(0,1,1)(1,1,0)[4]	918.59	924.14	ma1	est	-0.5175	4.27	Y	10.08	~~1794.82~~
				s.e.	0.1212				
			sar1	est	-0.6415	3.77	Y		
				s.e.	0.1702				

Source: Authors own computations

Next, residual diagnostic tests were conducted on the best fitted model (Table 9). No serial correlation was found to be present since the p-value of L-Jung Box Test > 0.05. The residuals were also found to be homoscedastic (p-value of ARCH-LM Test > 0.05). However, the residuals were not found to be normally distributed (p-value of Jarque-Bera test < 0.05).

Table 9: Residual diagnostic tests & plot (Units Series)

Type of Test	Name of Test	Output	Remarks
Serial Correlation	Box-Ljung Test	*p*-value = 0.2033	Absence of Serial Correlation
Constant Variance	ARCH-LM Test	*p*-value = 0.2991	Homoscedastic
Normality	Jarque-Bera	*p*-value < 2.2e-16	Absence of Normal Distribution

Source: Authors own computations

ARIMA (0,1,1)(1,1,0)[4] model cannot be claimed to be good as it did not satisfy all residual diagnostic tests as explained earlier. In the quest for generating a better model, the researchers tried for alternative models by log transforming the dataset and stationarity test suggests presence of it (p-value < 0.05). Mann-Kendall test recommends presence of trend (p-value < 0.05) and ETS test confirms seasonality (ETS(M,N,M) model). The comparison between the models chosen by AIC and BIC, shown in Table 10, indicates ARIMA(1,0,0)(1,1,0)[4] with drift to be the best model.

Table 10: Suggested ARIMA models based on AIC & BIC (log transformed series)

ARIMA Models	AIC	ARIMA Models	BIC
ARIMA(2,0,2)(1,1,1)[4] with drift	-40.1514	ARIMA(2,0,2)(1,1,1)[4] with drift	-25.1818
ARIMA(0,0,0)(0,1,0)[4] with drift	-18.5966	ARIMA(0,0,0)(0,1,0)[4] with drift	-14.8542
ARIMA(1,0,0)(1,1,0)[4] with drift	-44.4843	ARIMA(1,0,0)(1,1,0)[4] with drift	-36.9995
ARIMA(0,0,1)(0,1,1)[4] with drift	-35.2180	ARIMA(0,0,1)(0,1,1)[4] with drift	-27.7332
ARIMA(0,0,0)(0,1,0)[4]	19.7883	ARIMA(0,0,0)(0,1,0)[4]	21.6595
ARIMA(1,0,0)(0,1,0)[4] with drift	-37.2929	ARIMA(1,0,0)(0,1,0)[4] with drift	-31.6793
ARIMA(1,0,0)(2,1,0)[4] with drift	-43.6669	ARIMA(1,0,0)(2,1,0)[4] with drift	-34.3109
ARIMA(1,0,0)(1,1,1)[4] with drift	-43.6659	ARIMA(1,0,0)(1,1,1)[4] with drift	-34.3099
ARIMA(1,0,0)(2,1,1)[4] with drift	-41.7652	ARIMA(1,0,0)(2,1,1)[4] with drift	-30.5380
ARIMA(0,0,0)(1,1,0)[4] with drift	-20.7597	ARIMA(0,0,0)(1,1,0)[4] with drift	-15.1460
ARIMA(2,0,0)(1,1,0)[4] with drift	-43.3318	ARIMA(2,0,0)(1,1,0)[4] with drift	-33.9758
ARIMA(1,0,1)(1,1,0)[4] with drift	-43.0586	ARIMA(1,0,1)(1,1,0)[4] with drift	-33.7026
ARIMA(2,0,1)(1,1,0)[4] with drift	-41.5000	ARIMA(2,0,1)(1,1,0)[4] with drift	-30.2728
ARIMA(1,0,0)(1,1,0)[4]	-40.4932	ARIMA(1,0,0)(1,1,0)[4]	-34.8796
Best model ARIMA(1,0,0)(1,1,0)[4] with drift		Best model ARIMA(1,0,0)(1,1,0)[4] with drift	

Source: Authors own computations

Having chosen the model, the significance levels of the coefficients (ar1, sar1 and drift) were evaluated (Table 11). All coefficients are found to be significant with absolute values > 2. Also, the MAPE is found to be only 1.075, thus indicating a very good and highly accurate model. Investigation of residual diagnostics (Table 12) was done for the log transformed series. The p-values of L-Jung Box Test, ARCH-LM Test and Jarque-Bera test were all found to be > 0.05. Thus, it can be concluded that the residuals have no serial correlation, exhibits constant variance and are normally distributed. Absence of serial correlation was also verified from the correlogram of residuals (Figure 3(a) & (b)). Thus, ARIMA(1,0,0)(1,1,0)[4] with drift was accepted as the best fitted model among the ARIMA class of models.

Table 11: Summary of best fitted log transformed ARIMA model (AC&REF)

Model	AIC	BIC	Coeff.			t-Statistic	Sig.	MAPE
ARIMA(0,1,1)(1,1,0)[4]	-44.48	-37	ar1	est	0.7019	-6.08	Y	1.075
				s.e.	0.1155			
			sar1	est	-0.5035	3.33	Y	
				s.e.	0.1514			
			drift	Est	0.0531	4.87	Y	
				s.e.	0.0109			

Source: Authors own computations

Table 12: Residual diagnostic tests (log transformed)

Type of Test	Name of Test	Output	Remarks
Serial Correlation	Box-Ljung Test	p-value = 0.9864	Absence of Serial Correlation
Constant Variance	ARCH-LM Test	p-value = 0.7914	Homoscedastic
Normality	Jarque-Bera	p-value = 0.4592	Normally Distributed

Source: Authors own computations

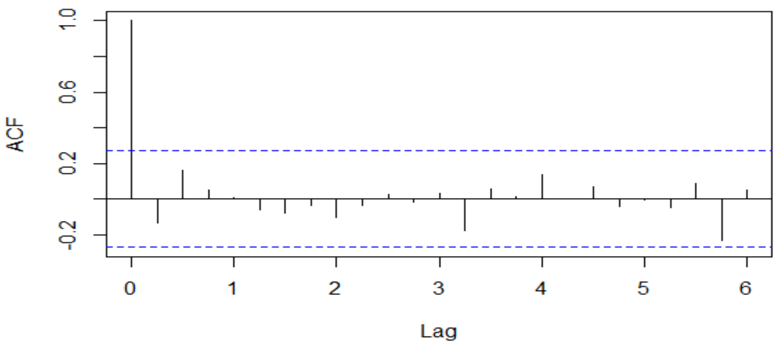

Figure 3(a): ACF of residuals (LTS)

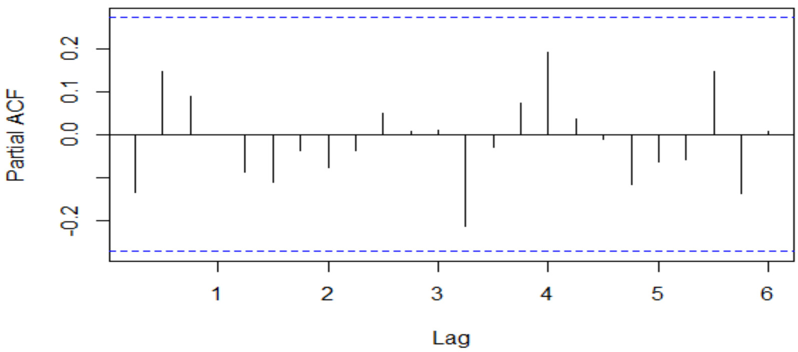

Figure 3(b): PACF of residuals (LTS)

Source: Authors own computations

3.3. Findings and analysis of triple exponential smoothing approach

TES with trend and additive seasonal component was compared with TES having trend and multiplicative seasonal component. While the former yielded alpha = 0.418 and coefficients a = 476940.71, b =-10693.22, s1 = 85488.97, s2 = 143536.43, s3 = -141405.93 and s4 = -100998.71, the latter yielded alpha = 0.453 and co-efficients a = 4.749477e+05, b = -1.029671e+04, s1 = 1.135462e+00, s2 = 1.265842e+00, s3 = 7.135127e-01, s4 = 7.915441e-01. The model accuracy estimates (MAPE) are shown in Table 13. Lower MAPE suggests TES with trend and additive seasonal component to be a better model than its multiplicative counterpart. The best model for forecasting was finally arrived at after checking the NNAR model and its accuracy estimates.

Table 13: MAPE of TES models

Model	MAPE
TES with trend and additive seasonal component	13.41
TES with trend and multiplicative seasonal component	15.39

Source: Authors Computations

3.3. Findings and analysis of neural network auto regressive modelling approach

The model identified is NNAR(1,1,2)[4]. Thus, NNAR(1,1,2)[4] indicates p=1, P=1 and k=2 i.e. the lagged inputs is of order 1, the lagged inputs of the seasonal component is of order 1 and the number of hidden layers is 2. The model has an average of 20 networks, each of which is a 2-2-1 networks. The accuracy estimate (MAPE) of the model is found to be 14.82.

3.4. Forecasting with the best model identified

At this stage the researchers made a forecast of the market size of AC&Ref industry till 2020 and using it market size growth was calculated. The model comparison is shown is Table 14. Comparison of the 6 alternative models indicate SARIMA model with log transformed dataset to be the best one with the lowest MAPE value.

Table 14: Model comparison between SARIMA, TES & NNAR

Model	MAPE
ARIMA(0,1,1)(1,1,0)[4]	10.08
ARIMA(0,0,1)(0,1,2)[4] with drift	61.36
ARIMA(1,0,0)(1,1,0)[4] with drift	1.075
TES with trend and additive seasonal component	13.41
TES with trend and multiplicative seasonal component	15.39
NNAR(1,1,2)[4]	14.82

Source: Authors own computations

Table 15: AC&Ref sales forecast in Mn INR (2018-2020)

FY Year & Qtr.		Point Forecast	Lo 80	Hi 80	Low 95	Hi 95
2018-19	Q1	530200.2	321656.7	873960.1	246883.0	1138645.6
2018-19	Q2	832742.7	475679.7	1457830.6	353648.9	1960872.3
2018-19	Q3	461926.0	252124.9	846317.6	182985.1	1166093.7
2018-19	Q4	465505.9	245249.2	883573.7	174693.8	1240444.1
FY 2018-19		2290374.8	1294710.5	4061682.0	958210.9	5506055.7
2019-20	Q1	626698.0	299191.8	1312704.4	202286.4	1941574.9
2019-20	Q2	910956.1	404343.5	2052317.1	263037.0	3154845.2
2019-20	Q3	502655.3	210978.2	1197563.9	133245.7	1896195.4
2019-20	Q4	501676.1	201531.3	1248820.4	124356.8	2023825.3
FY 2019-20		2541985.5	1116044.7	5811405.9	722925.9	9016440.8
2020-21	Q1	668131.3	246892.9	1808051.0	145759.0	3062554.7
2020-21	Q2	997612.3	345649.3	2879335.2	197221.0	5046320.9

2020-21	Q3	545321.1	179598.7	1655758.9	99761.7	2980823.0
2020-21	Q4	540975.9	171106.3	1710369.5	93030.3	3145772.4
FY 2020-21		2752040.6	943247.2	8053514.6	535772.0	14235471.0

Source: Authors own computations

The forecast values, both point forecast as well as forecast range at lower 80% and upper 95% confidence bands have been calculated (Table 15). The results indicate that the market size is expected to grow in the next three financial years till 2020. The MSG forecast is calculated next (Table 16). It shows a diminishing pattern from 2017-18 till 2020-21.

Table 16: Market size growth forecast of AC&Ref industry

Year	2017-18	2018-19	2019-20	2020-21
Market Size (Mn INR)	1948676.0	2290374.8	2541985.5	2752940.6
Market Size Growth		18%	11%	8%

Source: Authors own computations

3.5. Reliability of predicted market size growth

A series of technological innovations were launched in 2011-12 for air-conditioners and in 2013-14 for refrigerators after a substantial gap of more than 5 years (Table 3). After such breakthrough launches of multi-generation technology innovations, i.e. after 2013, it is clearly evident that both industry share and MSG of AC&Ref industry has improved, especially the former while the latter fluctuates in the last 5 years. While estimating reliability of MSG for three years, separate shape and scale parameters have been calculated with MSG data ranging from 2013-17, 2013-18 and 2013-19 respectively (Table 17). From Table 18 it is apparent that MSG forecast are not equally reliable for different years. The researchers have benchmarked more than 90% as high reliability and anything below it as low reliability. Iterative computations of reliability (Table 19) reveal MSG in 2018 over 2017 is reliable only at 11%, while it is 10% in 2019 over 2018 and 8% in 2020 over 2019.

Table 17: Shape & scale parameters of MSG

MSG Data Range for Parameter Estimation	Shape Parameter (β)	Scale Parameter (η)
2013-2017	1.96	37
2013-2018	1.9	34.29
2013-2019	1.72	31.08

Source: Authors own computations

Table 18: Reliability of MSG forecast

MSG Forecast Period	MSG Forecast %	$R(t) = \exp^{-(t/\eta)^\wedge\beta}$	Remarks
2018 over 2017	18	0.794	Low Reliability
2019 over 2018	11	0.892	Low reliability
2020 over 2019	8	0.903	High reliability

Source: Authors own computations

Table 19: MSG and reliability of at least 90%

Year	Growth %	Reliability
2018	17.5	0.79
	17.0	0.81
	16.0	0.83
	15.0	0.84
	14.0	0.86
	13.0	0.88

	12.0	0.90
	11.0	0.91
2019	11.0	0.89
	10.0	0.91
2020	8.0	0.90

Source: Authors own computations

4. CONCLUSION

The structure of domestic appliance industry in India has witnessed a huge metamorphosis in the last five years. This paper attempts to understand the behaviour of future growth of market size of AC&Ref industry in Indian context that is characterized by its growing dominance, erratic growth rates and launch of successive generations of technologies. Comparative forecasting approaches, both statistical and machine learning, have been used to select the best model for predictive purpose. Results reveal SARIMA model to be more effective compared to models generated from triple exponential smoothing and NNAR approaches. It also reveals that the researcher's concern on future market size behavior of AC&Ref industry in India is justified. From the study outcome it may be concluded that a year on year growth of market size is most likely till 2020. Also, the fluctuations seem to disappear but the growth rate is anticipated to exhibit a declining trend. This implies that diffusion of multi-generation technology innovation will face a gradual decline. Thus, organizations in this business need to focus on enhancing the rate of diffusion that would ultimately lead to product adoption. Market penetration seems to be an appropriate strategy for this. Sustained customer education on the key differentiating features is also considered vital. Alternative implication that may be contemplated is that in upcoming years the existing technology may lose its appeal of being perceived as radical innovations and further disruption in product advancements would be warranted. Finally, the researchers admit that this work cannot throw light on the rate of diffusion of the existing technology generations. Also, specific factors that might aid in maintaining the current growth pattern of market size remains undetected. These may be construed as limitations of this study which may be taken up for further research. The present work is expected to serve as a ready reckoner with empirical details on AC&Ref industry behaviour till 2020 and practitioners and decision makers may find it handy.

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