International Journal of Modern Agriculture
ISSN: 2305-7246
Volume 10 Issue 2, 2021

A Prediction of Waste Mobiles using Holt Trends Exponential Model

Swapnali Lotlikar[1],Dr. Ajay Khunteta[2], Dr.Mahesh Naik[3]
Research scholar[1], Professor[2]
[1&2]Poornima University, Jaipur(India)
[3]Assistant Professor,NMIMS (deemed to be University)
skhanolkar@rediffmail.com[1]

Abstract —The use of cell phones (smart phones) is quickly increasing at a great rate and correspondingly the e-waste produce from mobile is due to their short life spans. One of the factors for shorter life spans of mobile is the rapidly changing technology. In competitive mobile phone market, manufacturers are forced to add new features periodically making relatively newer phone obsolete. To support new features new hardware like sensors are added to the mobile increasing their complexity. This rapid change in mobile technology brings environmental issues since users scrap their mobile phone in a short span of time. This paper predicts the number of e-waste generated through scrapped mobile by 2024 using time series model.

Keywords-mobile scrap/trash;time series model; predict

I. INTRODUCTION

Time series analysisis generally used for a group of observations derived by calculating at regular intervalsin a time span. It depicts the historical report which changes over a time. This paper suggests Holt's Trend Exponential Smoothing modelfor e-waste prediction due to scrapped mobile phone.
Time series model have the smoothing boundary which are level and trend that are not saved by each other significance. It is known to be suitable for a series when seasonality is not therein data set and it consist of a linear trend

II. DATA COLLECTION

IDC publishes data every after three month cell phones sales data and the salesperson in India. This data / (report)was used as a secondary data / (report) source for the cell phones sales data in India. Source[IDC]

Table 1: Data of mobile sales (in millions)

	Quarterly data in millions			
Year	Q1	Q2	Q3	Q4
2010	25.53	38.63	40.08	45.76
2011	62.4	42.8	44.92	29.88
2012	48.8	51.24	42.82	57.14
2013	60.73	62	60.44	61.83
2014	60.05	63.21	72.5	74.24
2015	60.05	63.21	72.5	74.24
2016	52.8	61.2	72.3	58.7
2017	62.22	62	80	56
2018	54.3	74.2	82.2	68.5
2019	64.4	69.3	85	67
2020	55.3	28.2	80	43.9
2021	38			

The research shows that 32.92 % mobiles are refurbished, 29.59 % are recycled and 37.48% are scraped. [2] After applying 37.48% scrapped percentage on the above data, the scrapped mobiles mobile data was calculated. This is input data for Holt trend Time series model.

Table 2 : Data of Scrapped mobiles(in millions)

	Qtr1	Qtr2	Qtr3	Qtr4
2010	10.30700	10.30700	10.30700	10.30700
2011	15.57406	15.57406	17.30798	17.30798
2012	15.26643	20.17631	20.04769	23.79289
2013	29.98722	23.87406	26.70781	19.05836
2014	27.08245	25.47877	24.96448	29.80368
2015	30.97991	33.04897	32.85150	34.05361
2016	33.32145	34.90155	38.14242	39.31474
2017	35.06323	36.63352	38.71581	39.88491
2018	32.53469	36.06787	37.80846	33.87430
2019	35.76660	34.38902	41.75836	32.30967
2020	34.09849	38.44650	42.03378	38.33039
2021	37.97464			

III **FRAMEWORK AND ITS VERI FICA TION**

Linear trend model is been described by a time series getting high or low at a fixed range

$$y_t = \beta_0 + \beta_1 t + \varepsilon_t$$

Holt's trend exponential smoothing model can be used for time series survey when there is the change in boundary value of $\beta 0$ and $\beta 1$over a time

Note; Regression is been used when there is no change in the boundary value of $\beta 0$ or $\beta 1$ over a time$T$:

$\beta 0 + \beta 1T$is known as the level at a time

$\beta 1$ is known as the growth rate

IV Holt's Trend Exponential Smoothing model

Exponential smoothing model is used when the time series shows no trend. Holts model makes it possible to apply exponential smoothing to the time series data with trend.

The forecast equation is given by,

$$\hat{y}_{T+h|T} = l_T + hb_T$$

Where

$$l_T isthelevel \& b_T isthetrendestimate.$$

Level estimate

$$\ell_T = \alpha y_T + (1-\alpha)(\ell_{T-1} + b_{T-1})$$

Trend estimate

$$b_T = \gamma(\ell_T - \ell_{T-1}) + (1-\gamma)b_{T-1}$$

$\alpha = 0 \leq \alpha \leq 1$ [Denoted as constant for level]
$\gamma = 0 \leq \gamma \leq 1$ [Denoted as constant for trend]

Steps for the above method are as follow

Step 1: By connecting a least square trend lines to half of the past report obtain the estimates value of $\ell 0$ and $b0$

Step 2: Calculate the value of $y1$ from time 0.

Step 3: Change the value of $\ell_T$and $b_T$by using some pre-establish values of constant.

Step 4: Search the ideal integrationforα&γ to
reduce MSE / SSE

V THE PREDICTION MODEL
R code applied on the data produces the following results

Forecast method: Holt's method

Model Information:
Holt's method
Call:holt(y = AutoSales, h = 15)

Smoothing parameters:
α = 0.3397
γ = 0.0365

Initial states:
l = 8.4126
b = 1.0778

sigma: 3.3192

AIC : 285.0853
AICc : 286.6237
BIC: 294.1186

Error measures(Training set):
ME -0.4918501
RMSE 3.168226
MAE 2.350411
MPE -2.441372

International Journal of Modern Agriculture
ISSN: 2305-7246
Volume 10 Issue 2, 2021

MAPE 9.06642
MASE 0.8177214
ACF1-0.01292697

Level estimate
$\ell_T = 0.3397\, y_T + 0.6603\,(\ell_{T-1} + b_{T-1})$
Trend estimate:
$b_T = 0.0365\,(\ell_T - \ell_{T-1}) + 0.9635\, b_{T-1}$

Forecasts:

Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2021-Q2	38.92661	34.67292	43.18031	32.42115	45.43208
2021-Q3	39.19616	34.65145	43.74088	32.24563	46.14670
2021-Q4	39.46571	34.59374	44.33769	32.01467	46.91675
2022-Q1	39.73527	34.50197	44.96856	31.73164	47.73889
2022-Q2	40.00482	34.37842	45.63121	31.39999	48.60964
2022-Q3	40.27437	34.22529	46.32344	31.02311	49.52563
2022-Q4	40.54392	34.04464	47.04319	30.60414	50.48370
2023-Q1	40.81347	33.83834	47.78859	30.14594	51.48100
2023-Q2	41.08302	33.60806	48.55797	29.65106	52.51497
2023-Q3	41.35257	33.35528	49.34985	29.12178	53.58336
2023-Q4	41.62212	33.08131	50.16293	28.56007	54.68416
2024-Q1	41.89167	32.78728	50.99606	27.96770	55.81563
2024-Q2	42.16122	32.47421	51.84823	27.34621	56.97623
2024-Q3	42.43077	32.14298	52.71856	26.69695	58.16459
2024-Q4	42.70032	31.79439	53.60625	26.02114	59.37950

Table 3 : Forecast of Scrapped mobiles(in millions)

The above table displays the forecast values upto 4th quarter of 2024.It also shows high and low values with 80% and 95% confidence levels.

International Journal of Modern Agriculture
ISSN: 2305-7246
Volume 10 Issue 2, 2021

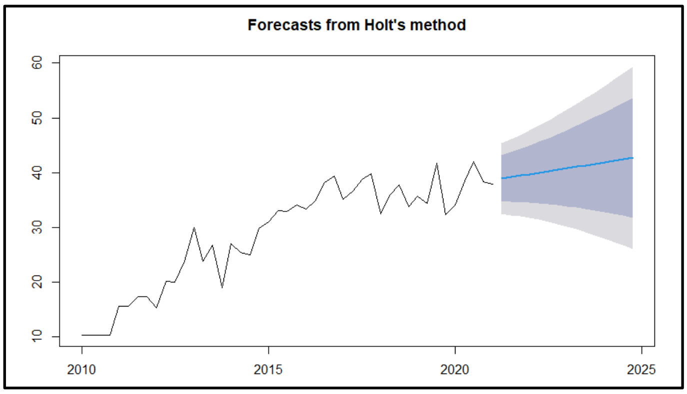

Figure 1: forecast from Holts method

In this figure we can visualize the trend of the cureent data and the forecast.The forecast shows upward trend.

Let us understand the forecast model with the help of various error measures.
Analysis of the error measures:

RMSE (Root Mean Square Error):RMSE defines the difference between model-predicted level andthe dependent series.
RMSE value (variation) in this case is 3.168226 which is relatively low.
MAPE (Mean Absolute Percentage Error):MAPE used to determined how much a series differ from its predicted series. MAPE value (variation) in this case is 9.06642
.
MAE (Mean absolute **error):**MAE used to calculate how much a series differ from its model-predicted level.
Mean absolute error is reported in the original series units.
MAE value (variation) in this case is 2.350411.

ACF1 Autocorrelation of errors at lag 1.
it is a measure of how much is the current value influenced by the previous values in a time series.
the correlation between a point and the next point is -0.01292697.Which almost no correlation.

Test for model validity : Ljung-Box test

The Ljung Box test is a way to test for the serial autocorrelation, up to a specified lag k.

The test determines whether or not errors are Independent and Identically Distributed. It checks whether or not the autocorrelations for the errors or residuals are non zero. It is a test of lack of fit: if the autocorrelations of the residuals are very small, then the model doesn't show 'significant lack of fit'.

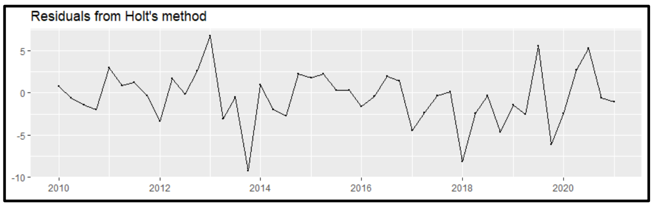

Figure 2: Residuals from Holts method

The Hypothesis of the Box Ljung Test is as follows,

H_0, is that our model *does not* show lack of fit.

H_a, is just that the model *does* show a lack of fit.

Also based on p value,
If **p-value** < 0.05: You can reject the null hypothesis assuming a 5% chance of making a mistake.
If **p-value** > 0.05: You don't have enough statistical evidence to reject the null hypothesis.

Test performed on the forecast yields the following:
Residuals from Holt's method
Q* = 8.5732,
df = 5,
p-value = 0.1273
Model df: 4. Total lags used: 9

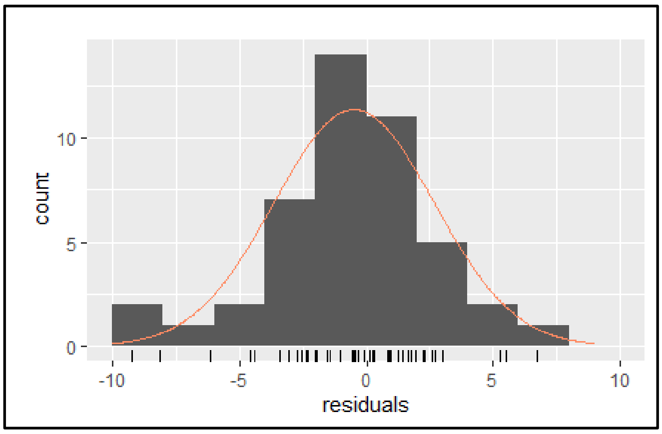

Figure 3: histogram

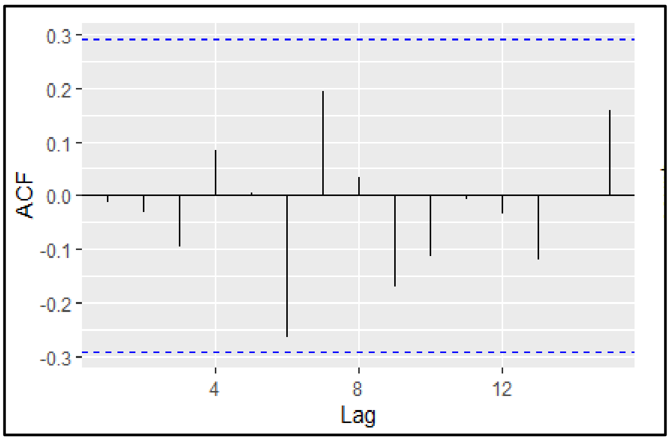

Figure 4: First order autocorrelation

p-value = 0.1273 thus,
since **p-value** > 0.05:

We don't have enough statistical evidence to reject the null hypothesis.

Thus we accept the null hypothesis.

Thus the forecasted model does not show lack of fit.

VI CONCLUSION

Applying Holt'strend time series to forecast the expected scrap for the future years was performed. The model was validated and shows a good fit as per As per Box Ljung Test. the graph in figure 1 shows that there is upward trendin time series, In the above data set , 42.7 million e-waste is forecasted value of scrap for the fourth quarter of year 2024 with maximum value of 59.37 million and minimum value of 26.02 million. with this forecast it becomes possible to take proper steps to handle the scrap generated.

References

[1] Wang, Fang, Lean Yu, and Aiping Wu. "Forecasting the electronic waste quantity with a decomposition-ensemble approach." Waste Management 120 (2021): 828-838.

[2] Lotlikar, Swapnali. "Future Forecasting Pollutants in Cell Phone Waste." (2017).

[3] Yuksel, Hilmi. "An analytical hierarchy process decision model for e-waste collection center location selection." In *Computers & Industrial Engineering, 2009. CIE 2009. International Conference on*, pp. 1684-1689. IEEE, 2009.

[4] Garg, Chandra Prakash. "Modeling the e-waste mitigation strategies using Grey-theory and DEMATEL framework." Journal of Cleaner Production 281 (2021): 124035..

[5] Zuo-yi, Xiang, and Zhao Feng. "Research on Waste Mobile Recycling Network Model and Application in the Context of E-commerce." In *E-Business and E-Government (ICEE), 2010 International Conference on*, pp. 803-807. IEEE, 2010.

[6] Perez, Patricio, and Jorge Reyes. "Prediction of particlulate air pollution using neural techniques." *Neural computing & applications* 10, no. 2 (2001): 165-171.

[7] Luo, Chunling, Chuanping Liu, Yan Wang, Xiang Liu, Fangbai Li, Gan Zhang, and Xiangdong Li. "Heavy metal contamination in soils and vegetables near an e-waste processing site, south China." Journal of hazardous materials 186, no. 1 (2011): 481-490..

[8] Han, Wei, Guanghai Gao, Jinyao Geng, Yao Li, and Yingying Wang. "Ecological and health risks assessment and spatial distribution of residual heavy metals in the soil of an e-waste circular

economy park in Tianjin, China." Chemosphere 197 (2018): 325-335.Ashish. Chaturvedi," The Carbon Footprint of E-Waste Recycling - Indian Scenarios", Gesellschaft fUr Internationale Zusammenarbeit, Germany, page 1-6 2004.

[9] Recycling in Korea with Emphasis on Extended Producer Responsibility (EPR)", IEEE International Symposium on Electronics and the Environment ,page 1-5, Scottsdale, AZ,2006.

[10] Jinhui Li ; Liu Hao ; Fengfii Yin , "An Agenda to Move Forward E-waste Recycling and Challenges in China ", Electronics and the Environment, IEEE International Symposium, Scottsdale, page no. 315 – 320,2006

[11] Ramzy Kahhat and Junbeum Kim, "Electronics and the Environment", Environmental research and education foundation Journal,page 181-185,2007.

[12] Guarnieri, Patricia, Lucio Camara e Silva, and Bárbara de Oliveira Vieira. "How to Assess Reverse Logistics of E-Waste Considering a Multicriteria Perspective? A Model Proposition." Logistics 4, no. 4 (2020): 25.

[13] Yang, Yang, Jian Zhang, and Weizhe Feng. "A prediction on electronic waste resource with time series model." In *Computer Application and System Modeling (ICCASM), 2010 International Conference on*, vol. 2, pp. V2-551. IEEE, 2010.

[14] Kiran, M., Prasanna Venkatesan Shanmugam, Atul Mishra, Abhang Mehendale, and HR Nadheera Sherin. "A multivariate discrete grey model for estimating the waste from mobile phones, televisions, and personal computers in India." Journal of Cleaner Production 293 (2021): 126185.