A Comparative Study of Demand Forecasting Using Winters Model and Neural Network for Automobile Sales during Lockdown in India – A Case Study

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Abstract— **Automobiles today need to forecast the future demand of the car to assist in decision making related to capacity expansion planning. One of the forecasting approaches that is based on judgmental or subjective factors is normally used to forecast the demand. As a result, demand could be overstock that eventually will increase the operation cost; or the company will face understock, which resulted in losing their customers. Due to the automotive industry is a very challenging process because of the high level of complexity and uncertainty involved in the system, an accurate tool to forecast the future of automotive demand from the modelling perspective is required. Hence, the main objective of this paper is to forecast the demand of automotive industries have the problem of medium to long-term sales forecasting raises several requirements that must be suitably addressed in the design of the employed forecasting methods. These include long forecasting horizons a high number of quantities to be forecasted, which limits the possibility of human intervention. The problem has been tackled by the use of Holt–Winter's method, as well as neural networks, applied to sales data from five companies.**

Index Terms— **COVID-19, Demand Forecasting, Automobile Sales, Winters Model, Neural Network.**

I. Introduction

Automobile is one among the successful corporate management sectors which depend on efficient strategic and operative planning. Planning plays a vital role in minimizing the errors, often leading to loss of cost and reputation as well. Efficient Planning can be achieved by making an effective contribution towards reliable forecasts. The reliability of forecasts has been increased these days which introduces the development of mathematical algorithms, combined with the utilization of computers. Data Mining and advanced technology are such methods which store the large amount of empirical data and evaluate such data sets to generate the means of producing more reliable forecasts. The explicability of a forecast model is very important as its reliability; in this paper the main objective is to present a model which is highly accurate and easily explicable for sales forecasts.

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The ability to forecast the future based on past data is a key tool to support organizational decision making. In particular the method of forecasting used most widely is the goal of Time Series Forecasting (TSF), which is to predict the behaviour of complex systems by analyzing the past patterns under same phenomenon. These traditional forecasting methods lack accuracy due to many limitations. The ability to capture subtle functional relationships among empirical data, to accommodate non-linear data, even where the underlying relationships are unknown; the Artificial Neural Network (ANN) algorithms have been found to be useful techniques for demand forecasting.

The Indian automotive industry, which was already battling a losing battle against low sales due to the increasing costs of introducing BS-VI and the losses incurred due to the inability to sell the old stock of BS-IV vehicles, now has two more troubles for its woes in 2020 – one against Covid-19's pandemic and lockdown and the other against weak consumer sentiment during these troubled times. Over the last two months, car manufacturers in India have faced the worst of an unimaginable scenario, with vehicle sales falling sharply.

Although domestic sales of vehicles fell to zero in April, the automotive industry witnessed a partial opening of production and sales in May, indicating that the road to recovery is a long battle. Overall sales decreased by almost 85 percent compared to May 2019.

II. LITERATURE REVIEW

i. Manda, et al. (2020)

This paper discusses how important the automotive sector is to the Indian economy and how the crisis can lead to different consequences, the primary objective of which was to study the slowdown in the industry and the effects of the slowdown and to identify potential solutions. The analysis uses descriptive research to gather information, analyse the past, document the current situation and explain potential outcomes. Finally, the paper suggests that severe economic push in the form of government initiatives is needed to revive the failed sector, otherwise the slowdown would continue. [1]

ii. Kochak Ashvin, et al. (2015)

The aim of the paper was to observe the performance of the forecasting of product demand by investigating it on a manufacturing company as a real-world case study. The results of the study indicated that, in this case, Artificial Neural Network performed more effectively than any other method of forecasting. The paper also proposes that this methodology can be considered as a successful decision support tool for forecasting and that future research can improve its accuracy. [2]

iii. L. Gaojun, et al. (2009)

The objective of this research was to combine multiple forecasting methods with a view to improving the car sales forecasting system. The paper combines the regression model, the time series model and neural networks using weight distribution in order to improve the problem of unilateralism. The results of the research suggested that this model would predict the number of car sales that would enable the company concerned to make appropriate and timely decisions. The manner in which the paper presented the neural networks and the combination of the predicted model can also be used for some other economic data. [3]

iv. Brühl, B. et al. (2009)

In this paper, the authors developed and tested various sales forecast models for the German automotive market. The main objective of the paper was to determine the best model to be used for prediction based on the quality of the results achieved. The time series model was based on the following: trend, seasonal, calendar and error components, while the latter three components were estimated univariately, the trend component was estimated using Multiple Linear Regression. The results of the research suggested that the non-linear model was found to be superior, as it provided the most accurate results for quarterly data. [4]

v. Fleurke, S. (2017)

The aim of this paper was to test in practice to what degree the ensemble forecast based on the combination of the results of multiple forecasting methods yields better results than a single forecast. As a result, the output of seven common forecasting methods is analyzed and the results are integrated into the Ensemble forecast. Thus, many common performance metrics are applied to the test data results and it is seen that the Ensembles perform significantly better independently than any of the forecasting models. [5]

III. METHODOLOGY

Forecasting a Time-series model predicts the systematic component of demand and estimates the random component. In its most general form, the systematic components of demand data contains: a level, a trend, and a seasonal factor. We estimate each of these parameters based on historical data and then use same values for all future forecasts. The equation for calculating the systematic component may take a variety of forms, as shown below.

- Multiplicative: Systematic component = level x trend x seasonal factor
- Additive: Systematic component = level + trend + seasonal factor
- Mixed: Systematic component = (level + trend) x seasonal factor

STEP – 1: Data Collection

This paper involves the analysis of data collected online for sales of cars from 5 automobile companies in India. The main time series comprises the number of registrations of new automobiles for every time period. The monthly sales of cars across different companies in India from JAN 2017 to MAY 2020 are considered. These data provide the information of initial estimates in order to find the desired optimized forecast model with accurate results.

STEP – 2: Time Series Forecasting Method – Holts winters model

Each Time series dataset can be decomposed to components which are Trend, Seasonality and Residual. Holt-Winters is one of the most popular forecasting techniques for time series. This method is decades old, but it's still ubiquitous in many applications; including monitoring- where it is used for purposes such as anomaly detection and capacity planning. Holt-Winters use exponential smoothing to encode lots of values from the past and use them to predict "typical" values for the present and future.

Steps in time series forecasting model using Holts winters model :

1. Compute initial estimates of the level, trend and seasonal factors.
2. Estimate error as the difference between the forecast and the actual demand.
3. Modify desired estimates in order to have overall estimate.
4. The tracking signal detects the consistency of forecasting method.
5. Comparing results for various factors.
6. Predicting accurate results for future estimates.

STEP – 3: ANN with combination of winters model

Artificial neural networks are forecasting methods that are based on simple mathematical models which allow complex nonlinear relationships between the response variable and its predictors. A neural network can be thought of as a network of "neurons" which are organised in many different layers. The predictors (inputs) form the bottom layer, and the forecasts (outputs) form the top layer. There may also be intermediate layers containing "hidden neurons".

Steps in time series forecasting model using Neural networks

1. Generating sample time series data
2. Configuring the time series prediction model
3. Training the model
4. Generating a single-step prediction
5. Predicting a single-step value
6. Multi-step time series predictions
7. Comparing results for different parameters
8. Ideas to further optimize the prediction model

A. STEP – 4: Data Analysis of individual Automobile Companies

B. Data Analysis Maruti Suzuki

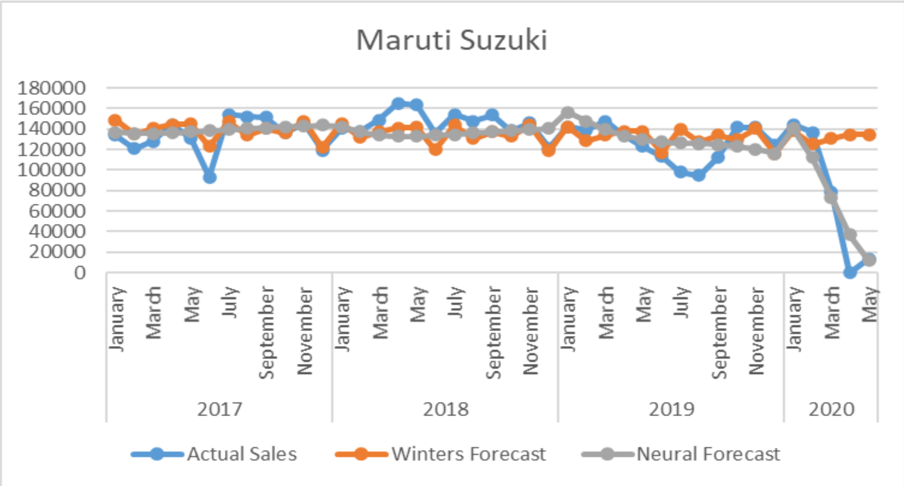

Fig. 1 Graphical Analysis of Maruti Suzuki

Table 1 Maruti Suzuki Data Analysis Table

Sl. No	Year	Month	Actual Sales	Winters Forecast	Neural Forecast
1	2017	January	133768	1,48,845	136725.42
2		February	120735	1,34,989	135569.22
3		March	127999	1,40,720	135514.8
4		April	144492	1,44,519	136103.93
5		May	130676	1,44,894	137024.83
6		June	93263	1,22,979	138084.24
7		July	154001	1,47,012	139169.42
8		August	152000	1,33,941	140218.01
9		September	151400	1,40,565	141197.88
10		October	136000	1,36,308	142094.59
11		November	145300	1,47,341	142903.83
12		December	119286	1,21,832	143626.98
1	2018	January	140600	1,45,348	142362.81
2		February	137900	1,31,812	137169.81
3		March	148582	1,37,402	134218.4
4		April	164978	1,41,104	133037.98
5		May	163200	1,41,464	133033.71
6		June	135662	1,20,062	133720.53
7		July	154150	1,43,518	134766.19
8		August	147700	1,30,751	135962.61
9		September	153550	1,37,210	137186.26
10		October	138100	1,33,049	138366.63
11		November	146018	1,43,811	139464.92
12		December	121479	1,18,907	140460.54
1	2019	January	142150	1,41,852	156162.19
2		February	139100	1,28,635	147330.26
3		March	147613	1,34,084	139332.69
4		April	133704	1,37,690	133411.87
5		May	123250	1,38,033	129701.82
6		June	113031	1,17,145	127655.84
7		July	98210	1,40,023	126565.56
8		August	94728	1,27,561	125799.37
9		September	112500	1,33,856	124834.47
10		October	141550	1,29,790	123207.04
11		November	141400	1,40,281	120444.18
12		December	124375	1,15,982	116001.49
1	2020	January	1,44,499	1,38,356	140750.07
2		February	1,36,849	1,25,458	112240.52
3		March	79,080	1,30,765	73660.361
4		April	0	1,34,275	37025.804
5		May	13,700	1,34,603	12018.762

Data Analysis Hyundai Motor Company

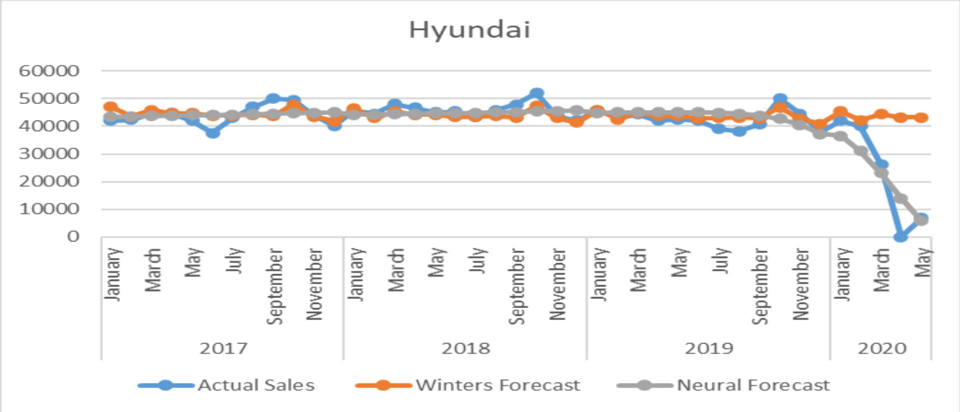

Fig. 2 Graphical Analysis of Hyundai Motor Company

Table 2 Hyundai Motor Company Data Analysis Table

Sl. No	Year	Month	Actual Sales	Winters Forecast	Neural Forecast
1	2017	January	42017	46941.21	43453.21
2		February	42327	43543.68	43563.54
3		March	44757	45872.43	43684.02
4		April	44758	44665.84	43814.25
5		May	42007	44692.74	43953.59
6		June	37562	43893.81	44101.14
7		July	43007	43939.68	44255.77
8		August	47103	44218.39	44416.12
9		September	50028	43762.95	44580.66
10		October	49588	47821.69	44747.7
11		November	44008	43582.84	44915.47
12		December	40158	41843.48	45082.2
1	2018	January	45508	46433.98	44159.37
2		February	44505	43072.74	44265.43
3		March	48009	45375.85	44381.13
4		April	46735	44181.88	44505.9
5		May	45008	44208.06	44638.95
6		June	45314	43417.36	44779.14
7		July	43481	43462.31	44925.07
8		August	45801	43737.55	45074.96
9		September	47781	43286.62	45226.65
10		October	52001	47300.72	45377.54
11		November	43709	43107.62	45524.37
12		December	42093	41386.81	45662.98
1	2019	January	45803	45926.74	44904.3
2		February	43110	42601.79	44977.54
3		March	44350	44879.27	45042.56
4		April	42005	43697.93	45088.2
5		May	42502	43723.37	45096.53
6		June	42007	42940.91	45038.77
7		July	39010	42984.93	44868.52
8		August	38205	43256.71	44510.2
9		September	40705	42810.3	43839.47
10		October	50010	46779.75	42650.11
11		November	44600	42632.39	40602.49
12		December	37953	40930.14	37168.11
1	2020	January	42002	45419.51	36549.9
2		February	40010	42130.85	31034.51
3		March	26300	44382.69	23183.97
4		April	0	43213.98	14012.28
5		May	6883	43238.69	5919.269

Data Analysis Mahindra & Mahindra Auto Company

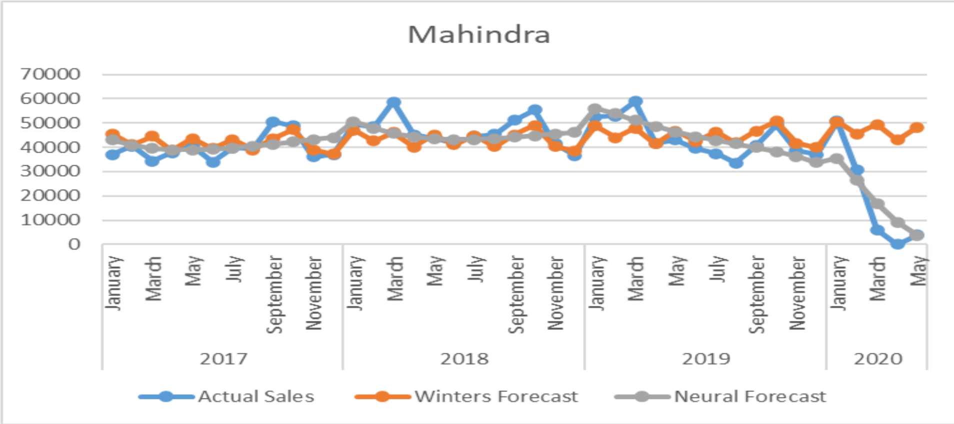

Fig. 3 Graphical Analysis of Mahindra & Mahindra Auto Company

Table 3 Mahindra & Mahindra Auto Company Data Analysis

Sl. No	Year	Month	Actual Sales	Winters Forecast	Neural Forecast
1	2017	January	37115	45,516	43047.673
2		February	40526	41,073	40950.584
3		March	34411	44,570	39613.573
4		April	37889	38,740	38971.996
5		May	40710	43,570	38882.679
6		June	33904	39,585	39193.19
7		July	39834	43,220	39773.413
8		August	39615	39,015	40523.161
9		September	50545	43,531	41369.354
10		October	48860	47,330	42260.285
11		November	36039	38,925	43160.095
12		December	36979	37,246	44044.392
1	2018	January	49432	47,188	50504.099
2		February	48473	42,578	47964.348
3		March	58652	46,197	45835.552
4		April	45217	40,151	44332.402
5		May	43818	45,152	43479.676
6		June	41689	41,017	43178.608
7		July	44605	44,779	43287.301
8		August	45373	40,419	43670.678
9		September	51268	45,093	44219.992
10		October	55350	49,022	44855.068
11		November	41564	40,312	45519.681
12		December	36690	38,570	46175.46
1	2019	January	52500	48,860	56100.577
2		February	52915	44,082	53803.827
3		March	59012	47,825	51214.537
4		April	41603	41,561	48642.602
5		May	43056	46,733	46349.683
6		June	39471	42,450	44434.842
7		July	37474	46,338	42836.773
8		August	33564	41,822	41401.034
9		September	40692	46,654	39942.644
10		October	49193	50,714	38280.683
11		November	38614	41,700	36253.244
12		December	37081	39,894	33727.924
1	2020	January	50785	50,533	35548.281
2		February	30637	45,587	26293.221
3		March	6130	49,453	16932.882
4		April	0	42,972	9173.485
5		May	3867	48,315	3731.609

Data Analysis Tata Motors

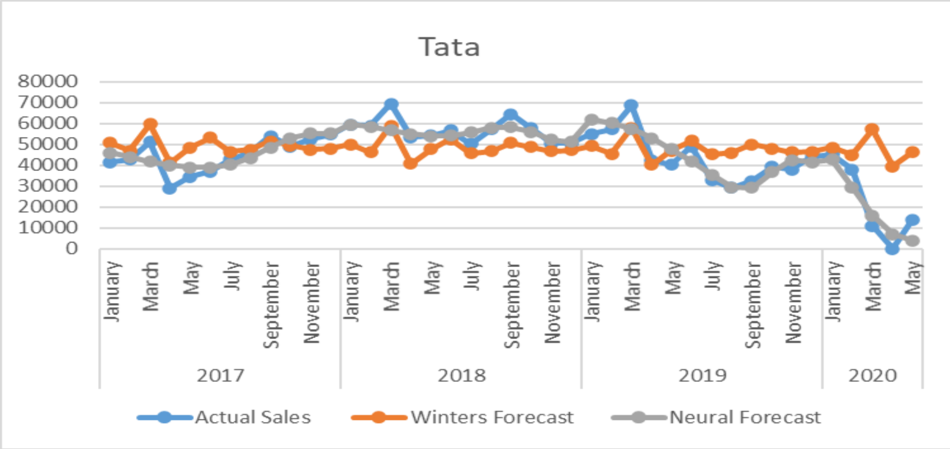

Fig. 4 Graphical Analysis of Tata Motors

Table 4 Tata Motors Data Analysis Table

Sl. No	Year	Month	Actual Sales	Winters Forecast	Neural Forecast
1	2017	January	41428	50,731	45875.68
2		February	42679	46,890	44046.34
3		March	51309	59,779	41825.06
4		April	28844	41,294	39929.6
5		May	34461	48,354	38879.44
6		June	36836	53,143	38868.13
7		July	42775	46,454	40237.36
8		August	45906	47,415	43567.82
9		September	53964	51,346	48560.36
10		October	48886	49,409	53042.73
11		November	52464	47,477	55252.54
12		December	54627	47,896	55311.78
1	2018	January	59441	50,005	59405.91
2		February	58993	46,218	58349.52
3		March	69409	58,922	56761.92
4		April	53511	40,701	55039.19
5		May	54290	47,659	53936.66
6		June	56773	52,378	54120.18
7		July	50100	45,784	55790.43
8		August	57210	46,731	57869.12
9		September	64598	50,604	58284.99
10		October	57710	48,695	56020.77
11		November	50470	46,789	52229.41
12		December	50440	47,202	51198
1	2019	January	54915	49,280	62020.3
2		February	57221	45,547	60312.41
3		March	68709	58,065	57404.14
4		April	42577	40,108	53050.2
5		May	40155	46,964	47703.79
6		June	49073	51,614	42003.39
7		July	32938	45,115	35567.58
8		August	29140	46,048	29440.79
9		September	32376	49,863	29157.9
10		October	39152	47,980	36765.43
11		November	38057	46,102	42465.17
12		December	44254	46,508	41492.52
1	2020	January	45,242	48,554	42634.34
2		February	38,002	44,876	29540.8
3		March	11,012	57,208	15933.61
4		April	0	39,516	6836.914
5		May	13,700	46,269	3970.236

Data Analysis Toyota Motor Corporation

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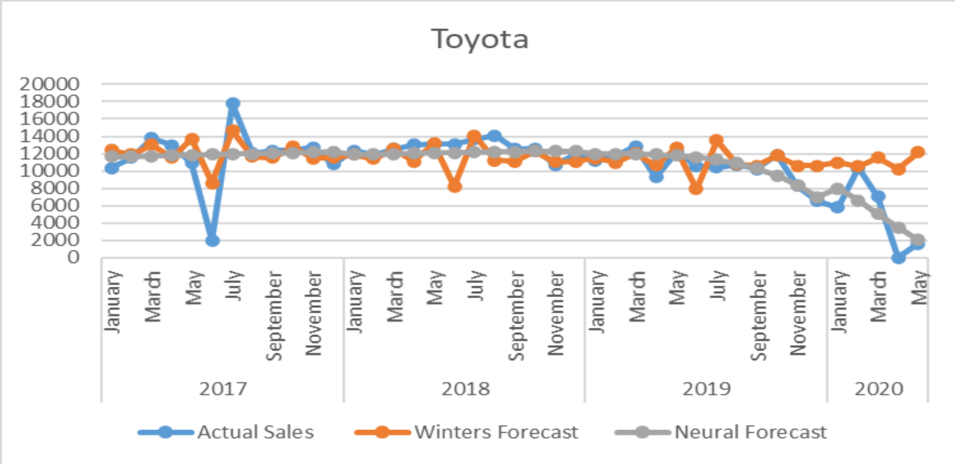

Fig. 5 Graphical Analysis of Toyota Motor Corporation

Table 5 Toyota Motor Corporation Data Analysis Table

Sl. No	Year	Month	Actual Sales	Winters Forecast	Neural Forecast
	2017	January	10336	12,387	11,639
2		February	11543	11,888	11,690
3		March	13796	13,049	11,741
4		April	12964	11,543	11,792
5		May	10914	13,712	11,843
6		June	1973	8,577	11,895
7		July	17750	14,672	11,947
8		August	12017	11,688	11,998
9		September	12335	11,519	12,050
10		October	12403	12,758	12,101
11		November	12734	11,497	12,151
12		December	10793	11,536	12,201
1	2018	January	12351	11,920	11,885
2		February	11864	11,438	11,935
3		March	12539	12,553	11,985
4		April	13037	11,103	12,033
5		May	13113	13,188	12,080
6		June	13088	8,248	12,125
7		July	13677	14,107	12,167
8		August	14100	11,237	12,205
9		September	12512	11,073	12,236
10		October	12606	12,262	12,259
11		November	10721	11,049	12,270
12		December	11836	11,085	12,263
1	2019	January	11221	11,452	12,003
2		February	11760	10,987	11,996
3		March	12818	12,057	11,963
4		April	9300	10,663	11,896
5		May	12138	12,664	11,779
6		June	10603	7,919	11,592
7		July	10423	13,543	11,307
8		August	10701	10,786	10,889
9		September	10203	10,627	10,292
10		October	11866	11,767	9,467
11		November	8312	10,601	8,373
12		December	6544	10,634	7,007
1	2020	January	5,804	10,985	8,000
2		February	10,352	10,537	6,627
3		March	7,023	11,562	5,069
4		April	0	10,223	3,485
5		May	1,641	12,140	2,057

IV. RESULT

The data of the five different automobile companies was analysed using both the methods. The results of the analysis show that the sales values forecasted by neural networks is more accurate than the ones forecasted by the winter's model. This indicates that artificial neural networks are data driven and more effective than the other method.

V. CONCLUSION

Demand forecasting is one of the main problems of supply chains to optimize stocks, reduce costs, and increase sales, profit, and customer loyalty. To overcome this issue, there are several methods such as time series analysis and machine learning approaches to analyse and learn complex interactions and patterns from historical data. This paper analyses the data of five automobile companies by Winter's model and artificial neural networks. As a result, the inclusion of deep learning approach reduced average prediction error for demand forecasting process and provided the accurate predictions equivalent to the future sales estimates.

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