# Hierarchical Forecasting and Reconciliation in the Context of Product Hierarchy

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**Abstract** -*Demand forecast of product and service is an important input for both long-range and short-range planning for organizations. In this study the focus is on forecasting of product hierarchies. The objective of present study is to find a suitable forecasting strategy when forecasts are required at several levels of product hierarchy and the individual product demand exhibit a seasonal pattern. Data employed for the study pertains to the sales data of car Industry. The study employs 6-year monthly data of total domestic sales company. Forecasting is essential for the 3 levels of hierarchy. Base level includes sales of Mini, Compact, Utility, and Vans. Middle level comprises sales of passenger car and passenger vehicles. Top level includes total domestic sale of company. The forecasting strategies deliberated in the project are; Top down, Bottom up and the optimal combination approach with Ordinary least square (OLS) for reconciliation. The performance of different strategies is compared using the Mean Absolute Percentage Error (MAPE). The Moving average, exponential smoothing techniques; single exponential smoothing, double exponential smoothing and triple exponential smoothing are used for forecasting individual series. The results show that the performance of bottom-up approach and Optimal combination approach is more or less same for the data series studied.*

***Key Words***: Hierarchical Time Series, Hierarchical Product Forecasting, Exponential smoothing, OLS Reconciliation

## 1. INTRODUCTION

Forecasting is a critical business process for nearly every organization and often it is the very first step organizations must undertake when determining long-term capacity needs, annual business plans, and shorter-term operations and supply chain. Forecasting is also important for production planning. Production managers need future demand forecast to plan and schedule a production and determine other related activities, like requirements planning and the application of forecasting in production and inventory, and proposed the "ideal" design of a forecasting system for production and inventory- control. Hierarchical forecasting has different forms pertaining to temporal and contemporaneous aspects. Here, we exclusively focus on contemporaneous hierarchies, specifically on products aggregated in groups and categories. This study summarizes the relevant theoretical background on hierarchical forecasting methods and the approaches of bottom-up, top-down, Optimal combination approaches for forecasting. We especially focus on the use of the hierarchical structure, product dependencies and heteroscedasticity in product demand, and critically evaluate approaches. Hierarchical product forecasting techniques should allow the product forecasts at each level to be summed giving the product forecasts at the level above.

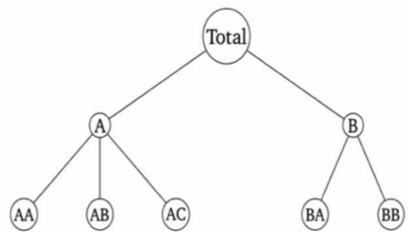


**Fig -1**: Example of a Product Hierarchy

By common method for product hierarchical forecasting, we first generate independent forecasts for each series at the bottom level of the hierarchy. Figure shows a simple product hierarchy. At the top level of the hierarchy is the Total, the most aggregate level of the product. This Product is break into two categories, A and B, which are in turn break into three and two subcategories respectively. Accurate demand forecasts lead to efficient operations and high levels of customer service, while inaccurate forecasts will inevitably lead to inefficient, high-cost operations and/or poor levels of customer service. Risk and uncertainty are central to forecasting and prediction; it is generally considered good practice to indicate the degree of uncertainty attaching to forecasts. In any case, the data must be up to date in order for the forecast to be as accurate as possible. The recognition of the best forecasting techniques is very crucial in the forecasting field, since the forecasts are used to drive the budget, distribution, and production planning processes. This study mainly aims to find the effective forecasting techniques and approaches of Hierarchical product time series on the basis of forecasts accuracy. made by different time series forecasting methods. So as to do this a large number of Hierarchical time series data is collected and forecasts are found out using various methods and strategies. Then we found the best and optimum forecasting approach for the data series studied. The data used in this study are real monthly sales data of organization

The main objectives of the study are as follows:

- To Create a set of product aggregation strategies to forecast the demand of product hierarchies corresponding to a specific class of data.
- Identify the different forecasting techniques through literature survey.
- Identifying the main determinants of forecasting accuracy through literature survey.
- Study the various techniques & strategy used for the forecasting specific class of data.

## 2. LITERATURE REVIEW

From the literature study, varying performance of the forecasting methods could be attributed to different statistical features of the data; a long forecasting horizon or a high degree of substitutability make Hierarchical Forecasting is better than Direct Forecasting. It is desirable that researcher examines all available literature both conceptual and empirical. The conceptual literature is one which deals with concepts and theories. Empirical literature is that which contains studies made earlier and so it consists of many facts and figures observed in the earlier study. A study of this literature enabling the researcher to know about the data and materials available for operational purpose. Review of literature shows the previous studies carried out by the researcher in this field. In the literature review, they are using simulated data or empirical data. In every organization supply Chain process, managers have special interest in acquiring information about future demand, disaggregated according to the information they need in order to plan the business processes. This is the point where hierarchical forecasting (HF) is needed [1]. Hierarchical time series represent multiple time series that are hierarchically organized and can be aggregated at several different levels in groups based on products and TD strategy consistently outperforms the BU strategy for forecasting product family [2]. The main criterion for selecting among different methodologies in hierarchical forecasting is the forecast accuracy. As a forecasting technique they mainly use Exponential Smoothing in product hierarchical forecasting and Study found that characteristics of demand can be significant in selecting appropriate forecasting strategies [3]. The reviewed paper shows that Bottom-up approach with Hybrid ARIMA-RBFNN modelling can be used for long-term predictions. As for the short and medium-term predictions, it can be used a bottom-up approach RBFNN modelling. Overall bottom-up approach with RBFNN modelling give the best result [4]. Combined forecast is not always the best forecasting method but the combined forecast is the most effective way to the relieve the forecasting risk [5] Integrated approach to forecasting hierarchical series demonstrates that forecast accuracy and inventory performance can be substantially improved with respect to other [6]. The top-down method performs better when data have high positive correlation compared to high negative correlation and combination of forecasting methods may be the best solution when there is no evidence of the correlation ship [7]. Optimal reconciliation models showed the best mean performance [8]. Forecasting literature show mixed results as to a preference for either top-down or bottom-up forecasting. This is not surprising as the performance of the approaches depends on the underlying demand process of products [9]. Due to the additive nature of the hierarchy, in which sums of product sales determine group sales, which, in turn, add up to determine category sales, the underlying demand process is transformed at various levels of the hierarchy [10]. Aggregation can lead to substantial information loss, which makes bottom-up forecasting seem favorable [14]. However, if no important information is lost, benefits can be gained if random noise cancels out, which makes top-down forecasting seem more favorable [11]. A wide variety of performance is seen as the nature and extent of differences between top-down and bottom-up are dependent upon context and the assumed demand processes [12]. Dependencies between the demand for different products are a key characteristic of the demand process, and hence a main driver of differences in performance between top-down and bottom-up approaches [13].

We can see that recent approach consists of forecasting all series at all levels of the hierarchy independently, followed by a regression model to optimally combine and reconcile these forecasts. From recent published paper we found that introducing a different approach in Product hierarchical forecasting, labelled the Optimal combination approach with reconciliation, which uses the hierarchical structure to create revised forecasts. This forecasting approach follows two steps: generate independent forecasts for each series in the hierarchy, weight these forecasts according to the hierarchical structure to determine the final forecasts. These final forecasts adhere to the hierarchical structure in the sense that aggregates of the forecasts at the bottom level exactly match forecasts at higher levels in the hierarchy. We concluded from the Literature review that top down and bottom-up approach are common in hierarchical forecasting so we are introducing new approach in product hierarchical forecasting is Reconciliation technique.

## 3. METHODOLOGY

Hierarchical time series forecasting is the process of generating coherent forecasts allowing individual time series to be forecast individually, but preserving the relationships within the hierarchy. In this study the focus is on the demand forecasting of hierarchies formed by aggregation of products. way of how the base forecasts is combined in order to produce revised forecasts. By base forecasts, we consider independent forecasts that are generated by some of the forecasting methods (for example: exponential smoothing, Moving Average).

The methodology for the study is as follows:

- Conduct literature review on existing forecasting techniques, strategies and reconciliation methodologies in the context of product hierarchy leading to, Identification of research gap and Problem definition
- Data Collection and Data analysis using different software's.
- Forecasting each of the series using different techniques like Moving average, single, Double, Triple Exponential smoothening.
- Forecasting of product hierarchy using Top Down, Bottom-Up & Optimal Combination approach
- Identification of Optimum strategy & reconciliation method for the series data.

Over 6 years of monthly sales data of different product data were collected. Collected data include domestic sales of the company. Data were analyzed and study the characteristics of data of four different products (Mini, Compact, Utility, Vans) which included in base level of hierarchy, Products groups (Passenger cars and Passenger vehicle) which included in Middle level and total domestic sales in Top level. Collected data divided into training and test sets. Three-year monthly sales data set as a training data used for setting and finding parameters for the specific data. One-year monthly data set as a test data, which is used for comparison and testing. Data were analyzed and found the components included in the data like trends, seasonal, irregularity, cyclical. Regression equation and trendline of the data were determined. we apply the different forecasting approach to real world sales data company. We then introduce the company and explain our study in which we compare the performance of the different approaches and techniques in product Hierarchical forecasting for the company data.

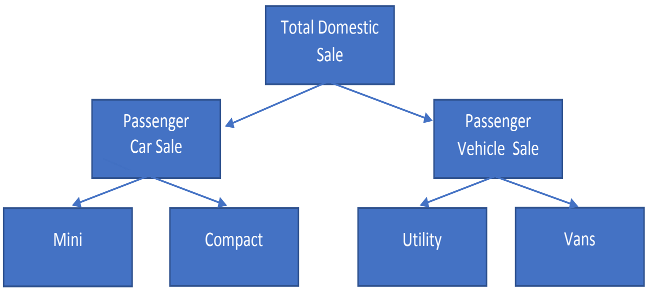


**Fig -2**: Product Hierarchy

For better understanding of the basic principles of HF, the diagram of the hierarchical structure is provided in Figure above. The diagram considers a hierarchy with K = 2 levels and n = 7 series in total. This study product hierarchy is as follows, Base levels are Mini, Compact, Utility, Van. In the middle level have two product groups are Passenger car & passenger vehicles. Top Level of the hierarchies is total domestic sale of the company. We plot charts, ACF, PACF for each node in product hierarchy using MS Excel, SPSS Software and go for detailed analysis of data of different products, product groups and product categories. After plotting the graph, we understand the trend and characteristics of each series of the product Hierarchy.

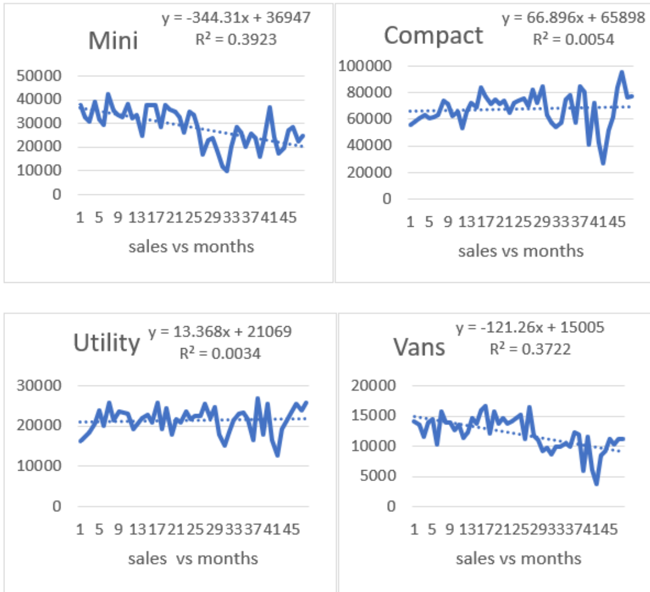


**Chart -1**: sales of base level products

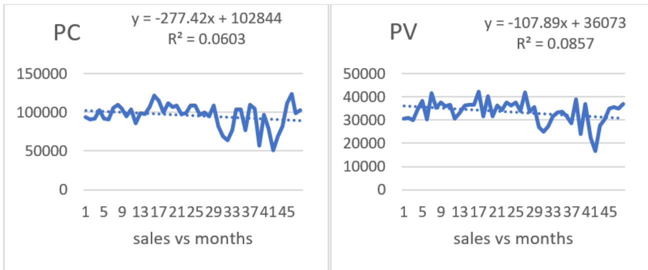


**Chart -2**: sales of middle level products

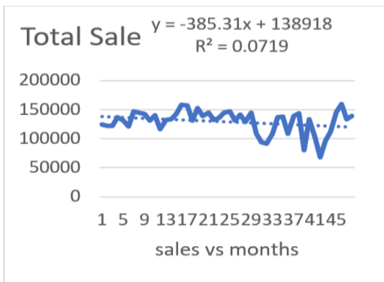


**Chart -3**: sales of Top level

### 3.1 Forecasting techniques

Moving average, Single exponential smoothing, double exponential smoothing, and triple exponential smoothing techniques are used for forecasting. The forecasts of individual nodes in each level were forecasted using the three methods. The individual forecasts then reconciled to generate more accurate forecast. Moving average, Single, double, and triple exponential smoothing are done using the forecast equations. α, ß, and Γ values are set for choosing best forecast.

*(i) Moving average*: - Moving average is one of the simplest forecasting techniques which forecasts the future value of a timeseries data using average (or weighted average) of the past 'N' observations. Mathematically, a simple moving average is calculated using the formula. The point forecasts are calculated as an unweighted average of the last k observations, as follows: -

$$F_{t+1} = \frac{1}{k} \sum_{i=t-k+1}^{t} X_i$$

*(ii)Single exponential smoothing*: - Single exponential smoothing assumes a fairly steady time-series data with no significant trend, seasonal or cyclical component. Here, the weights assigned to past data decline exponentially with the most recent observations assigned higher weights. In single ES, the forecast at time (t + 1) is given by (Winters, 1960)

$$F_{t+1} = \alpha Y_t + (1-\alpha)F_t$$

Parameter α is called the smoothing constant and its value lies between 0 and 1.

*(iii) Double exponential smoothing*: - Holt's method of double exponential smoothing is used in this study due to drawbacks of single exponential smoothing is that the model does not do well in the presence of trend. This can be improved by introducing an additional equation for capturing the trend in the time-series data. Double exponential smoothing uses two equations to forecast the future values of the time series, one for forecasting the level (short term average value) and another for capturing the trend.

Level (or Intercept) equation is (Lt): $L_t = \alpha Y_t + (1-\alpha)F_t$

The trend equation is (Tt): $T_t = ß(L_t - L_{t-1}) + (1-ß)T_{t-1}$

α and ß are the smoothing constants for level and trend, respectively, and $0 < \alpha < 1$ and $0 < ß < 1$.

*(iv) Triple exponential smoothing:* - In this study, Holt-Winter model of triple exponential smoothing are used for calculations. Single and double exponential smoothing techniques discussed so far can handle data as long as the data do not have any seasonal component associated with it. However, when there is seasonality in the time-series data, techniques such as moving average, exponential smoothing, and double exponential smoothing are no longer appropriate. In most cases, the fitted error values (actual demand minus forecast) associated with simple exponential smoothing and Holt's method will indicate systematic error patterns that reflect the existence of seasonality. For example, presence of seasonality may result in all positive errors, except for negative values that occur at fixed intervals. Such pattern in error would imply existence of seasonality. Such time series data require the use of a seasonal method to eliminate the systematic patterns in error.

Triple exponential smoothing is used when the data has trend as well as seasonality. The following three equations which account for level, trend, and seasonality are used for forecasting;

Level equation: $L_t = \alpha(Y_t/S_{t-c}) + (1-\alpha)[L_{t-1} + T_{t-1}]$

Trend equation: $T_t = ß(L_t - L_{t-1}) + (1-ß)T_{t-1}$

Seasonal equation: $S_t = \Gamma(Y_t/L_t) + (1-\Gamma)S_{t-c}$

The forecast $F_{t+1}$ using triple exponential smoothing is given by:

$$F_{t+1} = [L_t + T_t] * S_{t-c}$$

Where c is the number of seasons (if it is monthly seasonality, then c = 12; in case of quarterly seasonality c = 4; and in case of daily data c = 7).

### 3.2 Forecasting approaches for hierarchical time series.

This study mainly focused on Bottom-up, Top-down and Optimal combination approaches.

*(i) Top Down*: - The top-down approach aims to perform a forecast for the top level of the hierarchy ($\hat{y}_h$), and then disaggregate it to the different nodes by using a predefined proportion. The most common approach is the use of the average for each node, j, relative to its "parent" node as a proportion. For the top-down approach, the top-level revised forecasts are equal to the top-level base forecasts.

The equation for selecting the proportion ($p_j$) is given by;

$$p_j = \frac{1}{T} \sum_{t=1}^{T} \frac{y_{j,t}}{y_t}$$

For the hierarchy shown in Fig. 2, the predictions for the different nodes based on $\hat{y}_h$ are given by: $\hat{Y}_{PC,h} = p_{pc} \cdot \hat{y}_{sale\ h}$

$\hat{Y}_{PVh} = p_{pv} \cdot \hat{y}_{sale,h}$

$\hat{Y}_{mini,h} = p_{mini} \cdot \hat{y}_{PC,h}$

$\hat{Y}_{compact,h} = p_{compact} \cdot \hat{y}_{PC,h}$

$\hat{Y}_{utility,h} = p_{utility} \cdot \hat{y}_{PV,h}$

$\hat{Y}_{vans,h} = p_{vans} \cdot \hat{y}_{PV,h}$

*(ii) Bottom Up:* - Bottom-up (BU) approach first generates the base forecasts in the bottom level of the forecasting structure, using a forecasting model. All other forecasts in the structure are generated through aggregating of the base forecast to the higher levels, in a manner which is consistent with the observed data structure. This approach is generating the initial base forecasts at the lowest disaggregated level of the hierarchy (bottom level).so there isn't any loss of information from the data, which may occur when dealing with the data from more aggregate levels of the hierarchy, as in the case of top-down methodology. In this study, the calculations used for bottom-up approaches are;

$$\hat{Y}_{PC,h} = \hat{y}_{mini,h} + \hat{y}_{com,h}$$

$$\hat{Y}_{PV,h} = \hat{y}_{utility,h} + \hat{y}_{vans,h}$$

$$\hat{Y}_{sale,h} = \hat{y}_{PC,h} + \hat{y}_{PV,h}$$

*(iii) Optimal combination approach:* - The approach firstly considers generating the independent base forecasts for all nodes in the hierarchy. The problem with independent base forecasts is that they will not provide "aggregate consistency", since they will not sum up according to the hierarchy. This approach solves these issues by combining the base forecasts to produce a set of revised forecasts that are as close as possible to the independent forecasts, but also meet the requirement that forecasts at upper levels in the hierarchy are the sum of the associated lower-level forecasts.

$$\tilde{Y}_{n(h)} = SP\hat{Y}_{n(h)}$$

$$P = (S'S)^{-'}\, S'$$

### 3.3 Reconciliation

Reconciliation is the process of making the forecasts coherent. In this study, the reconciliation on hierarchical forecast is done using OLS (Ordinary least square) method. Reconciliation to hierarchical forecasting gives optimal combination approach. The OLS reconciliation technique is introduced by using programming language of python.

The convenient general matrix representation is;

$$Y_t = Sb_t$$

where S is a "summing matrix" of order m × n which aggregates the bottom level series to the series at aggregation levels above. Here the summing matrix in in the order of 7 x 4. The reconciliation is conducted by introducing a mapping matrix (P) in to the equation.

For this study, the matrix representation is;

$$\begin{pmatrix} Y_t \\ Y_{pc,t} \\ Y_{pv,t} \\ Y_{mini,t} \\ Y_{comp,t} \\ Y_{utility,t} \\ Y_{van,t} \end{pmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} Y_{mini,t} \\ Y_{compact,t} \\ Y_{utility,t} \\ Y_{vans,t} \end{pmatrix}$$

The hierarchical forecasting with reconciliation can then be written as,

$$\tilde{Y}_{n(h)} = SP\hat{Y}_{n(h)}$$

For some appropriately chosen matrix P. That is, existing methods involve linear combinations of the base forecasts. These linear combinations are "reconciled" in the sense that lower-level forecasts sum to give higher level forecasts. The effect of the P matrix is to extract and combine the relevant elements of the base forecasts, which are then summed by S to give the final revised hierarchical forecasts.

For OLS reconciliation;

$$P = (S'S)^{-'}\, S'$$

These equations are programmed in python. The hierarchical forecasts of each level are reconciled using python software. The reconciled forecasts then used for comparison to find optimum strategy.

Mean absolute percentage error (MAPE) is the average of absolute percentage error. Assume that the validation data has n observations and the forecasting is carried out on these n observations. The mean absolute percentage error is given by;

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|Yt-Ft|}{Yt} * 100$$

The equation is used for measuring the accuracy of the forecast. The forecast with minimum MAPE value is taken as best forecasting method. The MAPE value of each level are used for comparing the forecasting techniques and to develop a set of aggregation strategy.

## 4. RESULT AND DISCUSSION

The final results are based on accuracy of forecast methos and approaches that we performed during the study. Corresponding MAPE values for each node in the product hierarchy for the data set were calculated. Techniques and approaches with minimum MAPE value is taken as optimum method and approach for the product hierarchical forecasting. The comparison of each forecasting techniques and strategy using MAPE value in the context of product hierarchy is discussed in Tables below.

**Table -1:** MAPE (*100) Values of Base Level Forecast

| | Base Level Forecast | | | |
|---|---|---|---|---|
| | **Mini** | **Compact** | **Utility** | **Vans** |
| **Triple** | **0.05091** | **0.02792** | **0.02129** | **0.0346** |
| **Double** | 0.211183 | 0.163791 | 0.136537 | 0.1778 |
| **single** | 0.203318 | 0.18573 | 0.171613 | 0.17378 |
| **Moving** | 0.183553 | 0.167484 | 0.136982 | 0.164223 |

For base level, different products are Mini, Compact, Utility, Vans having different MAPE values for different methods but comparing with techniques like Moving Average Single, Double, Triple exponential smoothing, result shows that triple exponential smoothening is the most effective and best suited method for all series in base level of hierarchy, because it has less error accuracy measure MAPE.

**Table -2:** MAPE (*100) Values of middle Level Forecast.

| | Middle Level Forecast | | |
|---|---|---|---|
| | (*100) | **PC** | **PV** |
| **Triple** | MAPE | **0.03144** | **0.01884** |
| **Double** | MAPE | 0.13374 | 0.13702 |
| **single** | MAPE | 0.1304 | 0.13423 |
| **Moving** | MAPE | 0.1386 | 0.138 |

From the table above we found that error accuracy measure value of triple exponential forecasting technique is less for different middle level products groups. By comparing each series in the level, Passenger Car having MAPE value 0.03144 and Passenger Vehicle have MAPE value 0.01884. Least efficient method for the middle level of the product hierarchy is Moving Average method of Forecasting. Single and Double exponential have similar error accuracy.

**Table -3:** MAPE (*100) Values of Top-Level Forecast.

| | Top Level Forecast | |
|---|---|---|
| | (*100) | **Total Sale** |
| **Triple** | MAPE | **0.02487** |
| **Double** | MAPE | 0.12539 |
| **Single** | MAPE | 0.12405 |
| **Moving** | MAPE | 0.13019 |

The Top level of product hierarchy is total domestic sale of the company. By studying the table, we got that Triple exponential Smoothening is much better for forecasting with higher accuracy comparing to other methods. The MAPE value of total domestic sale is 0. 024870.Least accuracy method for the top-level forecast is Moving Average. Single and double having comparatively similar MAPE values so both have same effect on forecasting

Best Forecasting approaches or strategy for the different level in the hierarchy is discussed below and found the optimum forecasting approach for different levels

**Table -4:** MAPE (*100) values of different approaches in Base level. [TD-Top Down, BU-Bottom Up]

| | Base Level | | | |
|---|---|---|---|---|
| | **Mini** | **Compact** | **Utility** | **Vans** |
| **TD** | 0.245763 | 0.126917 | 0.122264 | 0.275491 |
| **BU** | **0.04719** | **0.02792** | **0.02129** | **0.03467** |
| **Optimal** | 0.04272 | 0.02923 | 0.024098 | 0.035907 |

**Table -5:** MAPE (*100) values of different approaches in middle level [TD-Top Down, BU-Bottom Up]

| | Middle Level | |
|---|---|---|
| | **PC** | **PV** |
| **TD** | 0.039622 | 0.078583 |
| **BU** | 0.033732 | **0.01748** |
| **Optimal** | **0.03207** | 0.019846 |

**Table -6:** MAPE (*100) values of different approaches in Top level [Optimal-Optimal combination approach]

| | Top Level |
|---|---|
| | **Total Sale** |
| **TD** | **0.024872** |
| **BU** | 0.026417 |
| **Optimal** | 0.025018 |

From this plotted tables we can understand that different approaches for base level of the product hierarchy having different accuracy and error. We tabulated the MAPE values for TD, BU and Optimal approach for products (Mini, Compact, Utility, Vans) specifically. From the result best strategy for base level of product hierarchy is Bottom-Up approach rather than Top down and Optimal combination. For a Middle level in product hierarchy, we can see that Optimal Combination approach and Bottom-Up approach is effective method for different products groups like Passenger car, passenger vehicle than Top down. The lowest MAPE values for passenger car and passenger vehicle is 0.032069 & 0.017477 respectively. For top level in product hierarchy, Total domestic sales having different data characteristics but comparing with different approaches, result shows that Top-Down is most effective method for top level in product hierarchy. Bottom Up and Optimal Combination approaches also have similar error accuracy measures compare to Top-Down. The study helps to develop a set of aggregation strategy to forecast the Total domestic sale of a organization for the period of 12 months in hierarchies based on Product aggregation corresponding to a specific class of product sales data of the organization. Total Domestic sale, Product group of passenger Car and Passenger vehicles and Products like (Mini, Compact, Utility, Vans) forecasts are calculated using the developed model for the test period and it is validated using actual data.

## 5. CONCLUSIONS

The main objective of the study was to develop a set of aggregation strategy to forecast the domestic product sale of a organization in hierarchies based on Product aggregation corresponding to a specific class of collected data. In this study, the best forecasting methods are identified in each node of each level and the best forecasting strategy are identified in each level. That is, the optimum forecast techniques and strategy for Individual products like (Mini, Compact, Utility, Vans) of test data set are developed. The approaches used are Bottom-up, Top-down and Optimal combination with Reconciliation. The forecasting techniques used are Moving average, single exponential smoothing, double exponential smoothing, and triple exponential smoothing. MAPE (error measure) is used for finding the best forecasting approach and best forecasting technique. From the study, results show that the best forecasting method for Base level, Middle level and Top level is Triple exponential smoothing compare to moving average, single and double exponential methods for the data series in the study. The forecasting approaches for each level are also identified. Performance of Optimal combination approach and bottom approach out performs the Top-Down approach on average and across all level product hierarchy. The result also shows that performance of bottom-up approach and Optimal combination approach is more or less same for the data series studied. This study was not focused on the, ARMA, ARIMA forecasting techniques and also approaches like modified top down, middle-out approaches. Similarly, there are different reconciliation techniques like OLS, WLS, Minimum Trace, etc. For this study, the OLS method of reconciliation is used. It can also be a limitation of the study. These all where the limitations of the study. The future work of the study relies on different areas like forecasting for intermittent demand data, forecasting for seasonal data using SARIMA models. Past 2 years Covid pandemic makes worst condition in automobile industry in India. So, our Hierarchical product forecasting will be effective in 3 different time periods. That is, pre-covid period (up to 2019), Pandemic period (2020 & 2021), and a post-covid period (Present year). For future works, suggestions include the time period of collected data is very important and amount of data for forecasting is very Crucial for efficient and better forecasting.

## REFERENCES

[1] Dejan Mircetic, Bahman Rostami-Tabar, Svetlana Nikolicic & Marinko Maslaric (2021), Forecasting hierarchical time series in supply chains: an empirical investigation -International Journal of Production Research.

[2] Petropoulos F., Makridakis S., Assimakopoulos V. (2014) "Horses for Courses" in Demand Forecasting", European Journal of Operational Research,Vol. 237, No.1, pp. 152–163

[3] Tiago Silveira Gontijo 1,* and Marcelo Azevedo Costa(2020), Forecasting Hierarchical Time Series in Power Generation, European Journal of Operational Research

[4] Mauro Costantinia,∗ , Carmine Pappalardob (2010), A hierarchical procedure for the combination of forecasts, International Journal of Forecasting 26 (2010) 725–743

[5] Seongmin Moon a,n , Christian Hicks b , Andrew Simpson (2012),The development of a hierarchical forecasting method for predicting spare parts demand in the South Korean Navy—A case study, Int. J. Production Economics

[6] Adya, M., Armstrong, J. S., Collopy, F., & Kennedy, M. (2000). An application of rule based forecasting to a situation lacking domain knowledge. International Journal of Forecasting, 16, 477–484.

[7] Assimakopoulos, V., & Nikolopoulos, K. (2000). The theta model: A decomposition approach to forecasting. International Journal of Forecasting, 16, 521–530.

[8] Rob J Hyndman, Roman A Ahmed & George Athanasopoulos (2010), Optimal combination forecasts for hierarchical time series

[9] Alysha M. De Livera and Rob J. Hyndman, (2012), Forecasting Time Series With Complex Seasonal Patterns Using Exponential Smoothing, Journal of the American Statistical Association

[10] Nikolaos Kourentzes, & Fotios Petropoulos (2016), Forecasting with multivariate temporal aggregation: The case of promotional modelling, Int. J. Production Economics

[11] George Athanasopoulos, Rob J. Hyndman, Nikolaos Kourentzes, & Fotios Petropoulos (2017), Forecasting with Product Hierarchies, Journal of Economic Surveys

[12] M. Zied Babai, Mohammad Ali (2019), The impact of temporal aggregation on supply chains, European Journal of Operational Research

[13] Dazhi Yang (2020), Reconciling solar forecasts: Probabilistic forecast reconciliation in a nonparametric framework, Solar Energy.

[14] Andrea Silvestrini & David Veredas (2008), Temporal aggregation of univariate and multi variate time series models: A survey, Journal of Economic Surveys.