(REFEREED RESEARCH)

RETAIL DEMAND FORECASTING IN CLOTHING INDUSTRY

KONFEKSİYON ENDÜSTRİSİNDE PERAKENDE TALEP TAHMİNLEMESİ

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ABSTRACT

Forecasting is the science of predicting future outcomes and, it is used to determine the future targets of a business, product, or industry in business life. It is extremely important for a business to do proper forecasting before developing new products or product lines and prevents spending a lot of time and money for developing a product that fails in the marketplace. In this study, three different quantitative forecasting models, simple moving average model, weighted moving average model and linear trend model are applied by using the past sales data of a well-known retailing brand in Turkey for forecasting sales.

Keywords: Demand forecasting, clothing industry, retail industry.

ÖZET

Tahmin gelecekteki çıktıları belirleme bilimidir ve iş hayatında bir işin, ürünün ya da sektörün geleceğe dönük hedeflerini belirlemede kullanılır. İş hayatında, yeni ürün veya ürün hatları geliştirmeden önce uygun bir tahmin yapmak pazarda başarısız bir ürün geliştirmeyi, zaman ve para harcamayı önlemede son derece önemlidir. Bu çalışmada Türkiye'de tanınmış bir perakende markasının geçmiş satış verileri baz alınarak üç farklı nicel tahminleme yöntemi ile, basit hareketli ortalama modeli, ağırlıklı hareketli ortalama modeli ve doğrusal eğilim modeli, kullanılarak satış tahminlemesi yapılmıştır.

Anahtar Kelimeler: Talep tahmini, konfeksiyon endüstrisi, perakende sektörü

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1. INTRODUCTION

Forecasting provides an estimate of future demand and the basis of planning and sound business decisions. Since all organizations deal with an unknown future, some error between a forecast and actual demand is to be expected. Thus, the goal of a good forecasting technique is to minimize the deviation between actual demand and the forecast. Since a forecast is a prediction of the future, factors that influence demand, the impacts of these factors, and whether these factors will continue to influence future demand must be considered in developing an accurate forecast [1].

Every apparel executive in the fields of product development, merchandising, marketing, and promotion is also a forecaster because those executives make decisions about an uncertain future with incomplete information. In companies today, forecasting must be a team effort, with information shared between design, merchandising, marketing, sales, and promotion, so that the right product gets produced and distributed at the right time to a target consumer. In the world of fashion, improving the success rate of new merchandise, line extensions, and retailing concepts by only a few percentage points more than justifies the investment of time and money in forecasting [2].

Short- and long-term forecasting has a different time horizon within the manufacturing cycle. The lynchpin in apparel planning and scheduling is the manufacturer. The forecast is a rolling one that begins with a long-term forecast-in this context a forecast is usually for 12 months but can be as short as 6 months to as long as 18 months. The forecast is developed by the sales and merchandising managers using input from retailers, marketing representatives, sales history analysis (one to three years of data), and market research. This working, long-term forecast mirrors the manufacturer's business expectations in terms of lines and styles to be produced each month. The short-term forecast includes both basic and fashion goods detailed down to weekly production by style, color, and size. Proper forecasting assures the timely delivery of merchandise to the retailer [3,4,5].

2. DATA WAREHOUSING AND DATA MINING IN FORECASTING

In addition to identifying and examining trends related to the general population, most retail decision makers, and specifically buyers, are now using techniques that allow them to identify, analyze, and take advantage of trends prevalent among their own customers. These techniques include data warehousing and data mining [6,7,8].

2.1. Data warehousing

Retailers have searched for ways to efficiently collect the wealth of information they gain from customers every day and to use that information to develop better retail strategies. Data warehousing involves electronically storing all this information. Retailers have generally used the data for financial and accounting purposes only and ignored the value of the data for marketing purposes. Typically, this data had been kept in many different computer systems. With data warehousing, there is only a single source of data. Data warehousing acts as a comprehensive single source for sales, margin, inventory, and other key merchandising performance measures.

2.2. Sales Forecasting

When developing a sales forecast, a step-by-step process should be followed that analyzes both internal and external forces that will affect sales [6]. This process involves the following steps:

1. Review past sales (past data).
2. Analyze changes in economic conditions.
3. Analyze changes in sales potential for specific products or markets.
4. Analyze changes in marketing strategies of your firm and the competition.
5. Forecast sales.

A review of past sales records will determine if there are any patterns or trends in the sales figures. Sales data will need to be compared with those of last month as well as last year during the same period. These data will give you an initial estimate of any change that might be expected during the coming year if everything else remains the same which rarely happens.

Sales forecasting methods can be basically divided into two categories such as qualitative methods and quantitative methods. Qualitative forecasting methods are approaches to forecasting based on intuition or judgmental evaluation and are generally used when data are limited, unavailable or not currently relevant [9]. While this approach can be very low cost, the effectiveness depends to a large extent on the skill and experience of the forecasters and the amount of relevant information available. The qualitative techniques are often used to develop long-range projections when current data is no longer very useful, and for new product introductions when current data does not exist.

Quantitative forecasting models use mathematical techniques that are based on historical data and can include casual variables to forecast demand [9]. Time series forecasting is based on the assumptions that the future is an extension of the past, thus, historical data can be used to predict future demand. Associative forecasting assumes that one or more factors (independent variables) are related to demand and, therefore, can be used to predict future demand. Since these forecasts rely solely on past demand data, all quantitative methods become less accurate.

Other forecasting models such as regression models, neural networks and fuzzy systems are not easy to use and suitable due to competitive environment, short life cycles, wide range of product types in textile and apparel retail industry. Several data mining techniques enable decision makers managing large volume of data, numeric or nominal [10].

The aim of this study to the literature is to present an appropriate tool for textile retail market for sales forecasting. Three quantitative forecasting models, simple moving average weighted moving average, weighted moving average forecasting and linear trend model were used to forecast sales using the past sales data of a well-known retailing brand in Turkey for forecasting sales.

3. METHODS

In this study, simple moving average weighted moving average, weighted moving average forecasting and linear trend models were used.

3.1. Simple Moving Average Forecasting Model

The method uses historical data to generate a forecast and works well when the demand is fairly stable over time [10]. Then n-period moving average forecast is,

$$F_{t+1} = \frac{\sum_{i=t-n+1}^{t} A_i}{n} \qquad (1)$$

Where;

F_{t+1} = forecast for Period t+1,

n = number of periods used to calculate moving average, and

A_i = actual demand in Period i.

The average tends to be more responsive if fewer data points are used to compute the average. However, random events can also impact the average adversely. Thus the decision maker must balance the cost of responding slowly to changes versus the cost of responding to random variations. The advantage of this technique is that is simple to use and easy to understand. A weakness of the simple moving average forecast is its inability to respond to tend changes quickly.

3.2. Weighted Moving Average Forecasting Model

The forecasting model which is based on an n-period weighted moving average follows [9]:

$$F_{t=1} = \sum_{i=t-n+1}^{t} w_i A_i \qquad (2)$$

Where;

F_{t+1} = forecast for Period t+1

n = number of periods used in determining the moving average,

A_i = actual demand in Period i, and

$w_i =$ weight assigned to Period i (with 1).

The weighted moving average allows greater emphasis to be placed on more recent data to reflect changes in demand patterns. Weights used also tend to be based on experience of the forecaster. Although the forecast is more responsive to underlying changes in demand, the forecast still lags demand because of the averaging effect. As such, the weighted moving average method does not do a good job of tracking trend changes in the data.

3.3. Linear trend forecasting model

The trend can be estimated using simple linear regression to fit a line to a time series of historical data. The linear trend method minimizes the sum of squared deviations to determine the characteristics of the linear equation, or

$$\hat{Y} = b_0 + b_1 x \tag{3}$$

Where;

$\hat{Y}$ = forecast or dependent variable

x = time variable,

b_0 = intercept of the line, and

b_1 = slope of the line

The coefficients and are calculated as follows:

$$b_1 = \frac{n\sum(xy) - \sum x \sum y}{n\sum x^2 - (\sum x)^2} \; and$$

$$b_0 = \frac{\sum y - b_1 \sum x}{n} \tag{4}$$

Where;

b_1 = slope of the line,

x = independent variable values,

y= dependent variable values,

$\bar{x}$ = average of the x values,

$\bar{y}$ = average of the y values, and

n = number of observations.

In order to apply the theoretical methods mentioned above to practical cases, we worked with the past sales data which are taken from the well-known and leading brand in the fashion industry in Turkey with its 99 stores and 123 franchised stores and outlets. Each week 75 new models along with 12 collections consisting of each year's spring-summer and autumn-winter main collections and also along with mid-season collections which are prepared once a month throughout the mid-season period are displayed in the companies' stores with their "fast fashion" philosophy. Table 1 shows the sales data of the company between January 2007 and April 2009.The sales data is important because it shows the decrease of sales when the world economic crisis began in 2009.

Table 1. Past sales data between January 2007-April 2009

		SHIRT	JEANS	PANTS	WOMEN SHIRT	WOMEN JEANS	WOMEN PANTS	SKIRT
2007	January	11.937	16.542	7.166	12.330	11.752	8.971	10.874
	February	22.785	22.842	11.435	23.773	12.162	11.246	15.318
	March	25.707	30.471	17.445	24.295	12.234	16.424	19.102
	April	23.229	29.483	17.941	24.183	11.717	18.508	12.154
	May	31.252	25.143	18.037	30.740	10.502	17.501	12.420
	June	70.478	31.217	27.438	36.473	10.570	14.141	14.630
	July	49.525	24.657	14.649	28.811	13.178	11.383	15.465
	August	53.709	29.038	21.122	38.781	20.635	17.295	29.361
	September	51.465	32.882	22.884	40.723	28.040	15.740	24.841
	October	35.695	39.888	22.460	21.969	24.563	19.998	14.944
	November	17.329	17.536	14.154	10.889	9.904	9.739	7.851
	December	31.251	40.501	30.211	12.612	22.928	25.793	11.167
2008	January	30.664	26.556	27.740	12.391	13.954	20.851	12.686
	February	34.104	35.327	21.941	16.720	14.041	20.106	12.157
	March	31.458	26.444	22.584	24.777	15.076	12.675	13.945
	April	44.534	29.188	25.221	34.191	14.274	14.383	15.311
	May	54.317	29.342	23.041	36.429	12.468	28.977	18.422
	June	76.382	26.455	31.825	29.448	9.926	28.302	22.695
	July	60.470	25.304	27.647	29.592	10.714	23.177	24.209
	August	58.945	29.195	24.166	35.256	13.333	19.186	23.732
	September	55.504	49.433	24.365	28.424	24.471	24.242	17.431
	October	22.746	17.444	10.664	12.407	10.272	11.888	7.747
	November	29.049	25.522	16.125	11.638	12.801	9.017	9.482
	December	28.862	33.740	24.698	17.385	17.283	12.897	9.746
2009	January	18.860	22.844	25.910	15.598	17.521	13.320	9.046
	February	28.005	27.069	13.274	13.642	16.270	14.491	13.425
	March	26.736	25.036	13.410	13.315	16.121	10.269	11.377
	April	34.540	23.819	18.100	11.182	15.878	11.330	14.506

4. RESULTS AND DISCUSSION

4.1. Discussion of Past Sales Data

In the monthly sales graph of shirts as seen in Figure 1, for the years 2007, 2008 and beginning of 2009, it is seen that there are two peak points in sales in June. The reason for this might be that, the firm continues to sell some basic types of shirts of autumn-winter season and besides, with the beginning of spring-summer season, the sales of short-sleeved, summer models are also increased and especially in June the sales reach the maximum points. As a result, when the next autumn-winter season starts, the sales of shirts decrease due to the fact that the models of summer are not preferred by customers anymore.

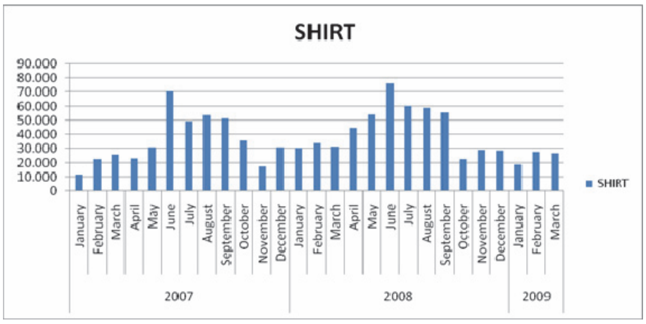

Figure 1. Monthly Past Sales Data for Shirt

As it is seen in Figure 2 and Figure 3 the sales graphs of jeans and women jeans show that the sales are proportionally distributed because in every season, jeans are preferred by every age group of people. However, there are some peak points which are caused by the passing period between spring-summer and autumn-winter seasons.

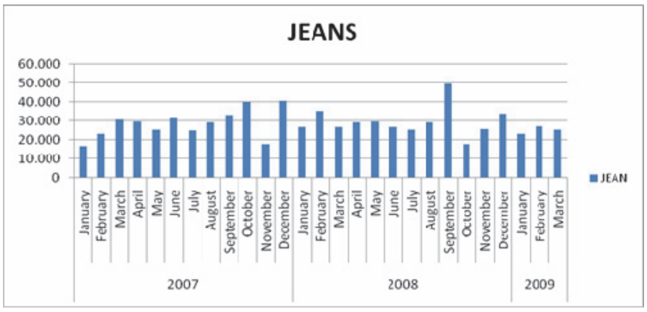

Figure 2. Monthly Past Sales Data for Jeans

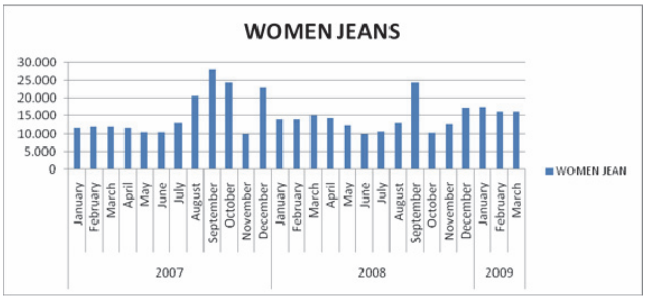

Figure 3. Monthly Past Sales Data for Women Jeans

Figure 4 indicates the monthly sales of shirts for the years 2007, 2008 and beginning of 2009, it is seen that there is an increase in the sales through the spring-summer season. The reason for this situation might be that the demand for summer models is higher because of the weather conditions.

Figure 4. Monthly Past Sales Data for Women Shirt

In the sales graph of pants, it is seen that in the November, there are a sharp decrease in sales as seen in Figure 5 and Figure 6. It can be said that the reason of this reduction is changing of seasons. In summer season the pants models are more vaporous than the other seasons' models. However, at the end of the summer season, the firm does not put up the new, autumn- winter season models (courser models) for sale. It is made for making customers have tendency to buy the last summer season products. Because, before passing through the new season the firm wants to finish the sale of the last season. So that, the sales of pants in the beginning of the new autumn- winter season would be lower.

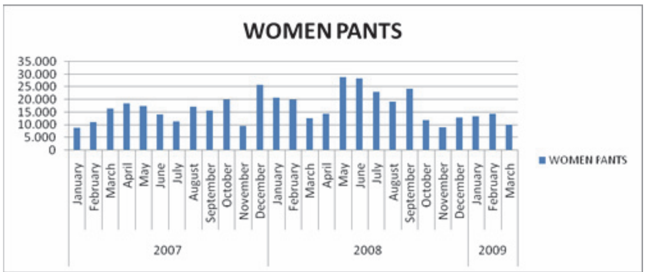

Figure 5. Monthly Past Sales Data for Women Pants

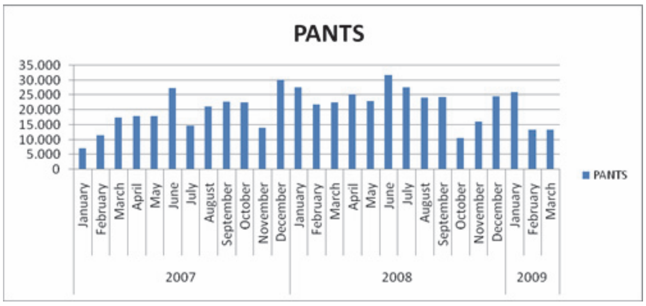

Figure 6. Monthly Past Sales Data for Pants

In Figure 7, it is seen that the sales of skirts increased in summer from the sales data. Women prefer wearing skirt in summer much more than in winter season because in winter the weather condition is not suitable for wearing skirts due to the cold whereas in summer wearing skirts feels more comfortable and fresh.

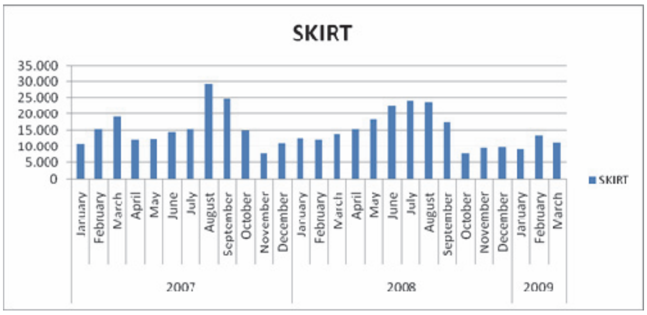

Figure 7. Monthly Past Sales Data for Skirt

4.2. Discussion of Forecasts

While applying forecasting by simple moving average model, Equation (1) is used. Table 2 Table 3 and Table 4 show the results obtained by using simple moving average model, weighed moving average model and linear trend forecasting model for sales 2009 March and April.

In Figure 8 and Figure 9, the comparison of the actual sales data and forecasted sales data are presented for March 2009 and April 2009 considering simple moving average model. The forecasts for women's jeans are convenient with the actual data for all two graphs. For simple model average model, the deviation from the forecasted values for pants model are maximum and for women's jeans are minimum for March. For skirt and shirt models forecasted sales are also lower than the actual sales and it also creates problem during the March season. Moreover, when April forecasts evaluated, it is seen that, for women's jeans and pants the deviations from actual sales are quite small but for shirt model it is bigger. Also for shirt and skirt models forecasted sales values are less than actual values.

Table 2. Forecasting by Simple Moving Average Model

	SHIRT	JEAN	PANTS	WOMEN SHIRT	WOMEN JEAN	WOMEN PANTS	SKIRT
Forecast March	26194	27294	20002	14566	15969	12431	10425
MARCH Actual	26736	25036	13410	13315	16121	10269	11377
Forecast April	25616	27172	19323	14985	16799	12744	10899
APRIL Actual	34540	23819	18100	11182	15878	11330	14506

Table 3. Forecasting by Weighted Moving Average Model

	SHIRT	JEANS	PANTS	WOMEN SHIRT	WOMEN JEANS	WOMEN PANTS	SKIRT
Forecast March	27652	28969	21603	14473	16052	16136	11264
MARCH Actual	26736	25036	13410	13315	16121	10269	11377
Forecast April	28281	27861	19873	16033	16068	14586	11969
APRIL Actual	34540	23819	18100	11182	15878	11330	14506

By using Equation (3), the coefficients and are calculated and given in Table 4 and Table 5 the Y values show the forecasts.

Table 4. Forecasting by Linear Trend Model for March

	(Shirt)	(Jean)	(Pants)	(Shirt Lady)	(Jean Lady)	(Pants Lady)	(Skirt)
$\sum x$	351	351	351	351	351	351	351
$\sum x^2$	6201	6201	6201	6201	6201	6201	6201
$(\sum x)^2$	123201	123201	123201	123201	123201	123201	123201
$\sum(x^*y)$	13881823	10199892	7715273	8001289	5378457	6099675	5243066
N	26	26	26	26	26	26	26
b_o	34653.5908	27186.66	17519.26	27816.658	14048.76	15490.09	16533.34
b_1	277.118632	106,0113	0.047901	-284.2055	72.14051	106.8626	-90.32
Y	42136	30049	17521	20143	15997	18375	14094
Actual sales	26736	25036	13410	13315	16121	10269	11377

Table 5. Forecasting by Linear Trend Model for April

	(Shirt)	(Jean)	(Pants)	(Shirt Lady)	(Jean Lady)	(Pants Lady)	(Skirt)
$\sum x$	378	378	378	378	378	378	378
$\sum x^2$	6930	6930	6930	6930	6930	6930	6930
$(\sum x)^2$	142884	142884	142884	142884	142884	142884	142884
$\sum(x^*y)$	14603695	10875864	8077343	8360794	5813724	6376938	5550245
N	27	27	27	27	27	27	27
b_o	35794.3162	27577.9858	18328.74	28322.444	14039.54	16090.56	16734.63
b_1	154.898	66.226	165.81	-338	73.13	42.53	-111.897
Y	40131	29412	22971	18847	16017	17281	13601
Actual sales	34540	23819	18100	11182	15878	11330	14506

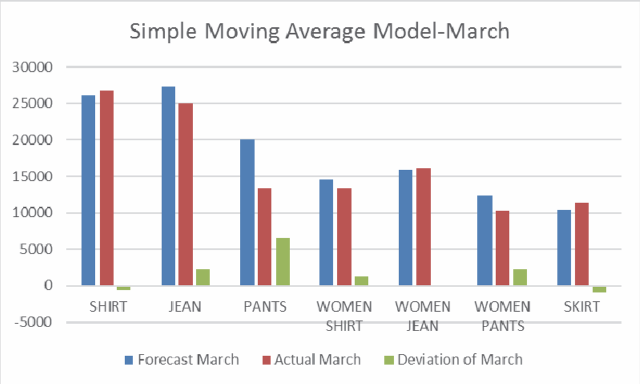

Figure 8. Comparison of Actual Sales and Forecast by Simple Moving Average Model for March

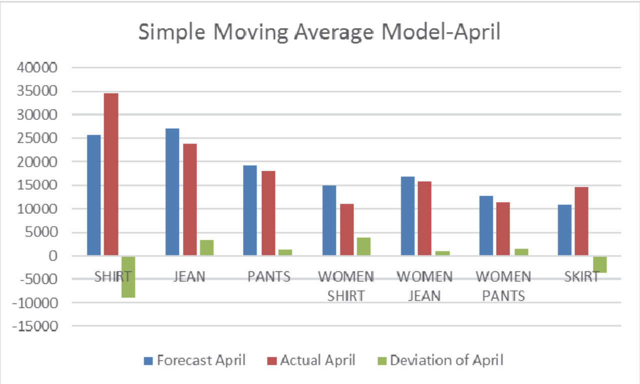

Figure 9. Comparison of Actual Sales and Forecast by Simple Moving Average Model for April

In Figure 10 and Figure 11 give the comparison of the actual sales and forecasted sales data made for March 2009 and April 2009 using weighted moving average model. The forecasted values for women's jeans are obtained very close to the actual sales data for two months. Deviations of forecasts for pants and women's pants models are obtained maximum. For women's jeans and skirt models deviations from forecasted values are minimum and also less than actual sales for March. Moreover when April forecasts are considered, for shirt and women's shirt, the deviation is quite big. Also again for shirt and skirt forecasted sales values are less than actual sales values.

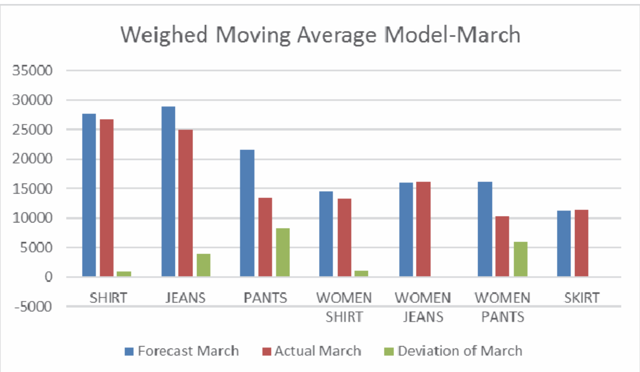

Figure 10. Comparison of Actual Sales and Forecast by Weighted Moving Average Model for March

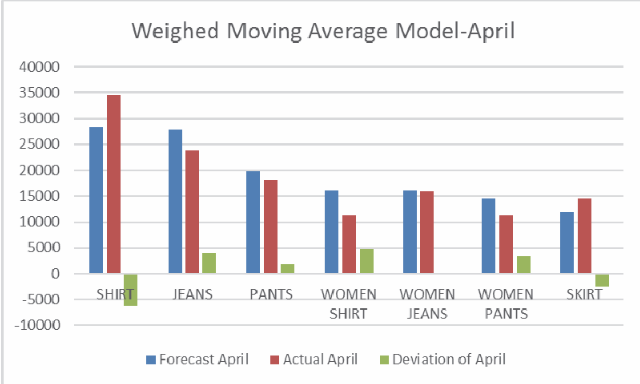

Figure 11. Comparison of Actual Sales and Forecast by Weighted Moving Average Model for April

In Figure 12 and Figure 13 show the comparison of the actual sales and forecasted sales data made for March 2009 and April 2009 using linear trend model. The forecasted values for women's jeans are again obtained very close to the actual sales data for two months. Deviations of forecasts for shirt and women's pants models are obtained as maximum. Moreover when April forecasts are considered, for women's shirt and women's pants, the deviation is quite big. Also for women's skirt, forecasted sales values are less than actual sales values.

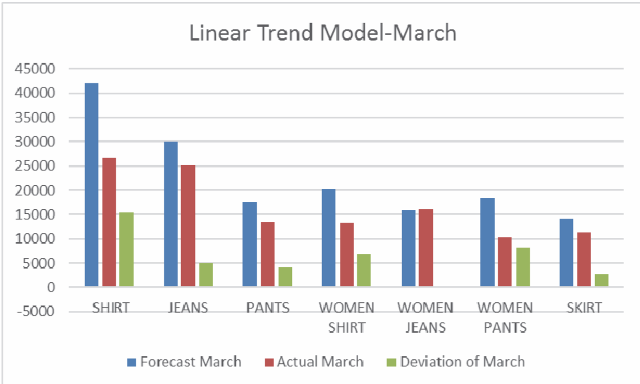

Figure 12. Comparison of Actual Sales and Forecast by Linear Trend Model for March

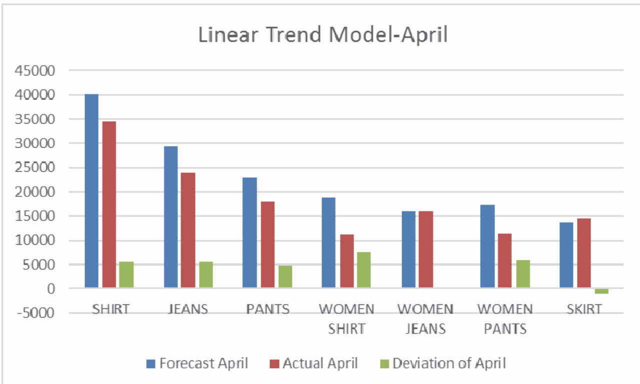

Figure 13. Comparison of Actual Sales and Forecast by Linear Trend Model for April

Table 6 shows the correlation values for actual sales values and forecasted sales values. High correlation values obtained for actual sales and forecasted sales values.

Table 6. Correlations for actual sales and forecasted sales

Paired Samples Correlations				
		N	Correlation	Sig.
SMAM	actual_sales_in_march & forecast_in_march	7	0.924	0.003
SMAM	actual_sales_in_april & forecast_in_april	7	0.845	0.017
WMAM	actual_sales_in_march & forecast_in_march	7	0.884	0.008
WMAM	actual_sales_in_april & forecast_in_april	7	0.883	0.008
LTM	actual_sales_in_march & forecast_in_march	7	0.904	0.005
LTM	actual_sales_in_april & forecast_in_april	7	0.940	0.002

SMAM: Simple Moving Average Model, **WMAM**: Weighted Moving Average Model, **LTM:** Linear Trend Model

Also a method, called the least-squares method was used to make an analysis of errors made in using three different methods to forecast real sales data (Figure 14). As seen from the figure, for March the smallest amount of error obtained for simple moving average model and for April it was obtained for weighted moving average model. Linear trend model always gave the highest error. Weighed moving average model had the similar amount of error considering both months, March and April.

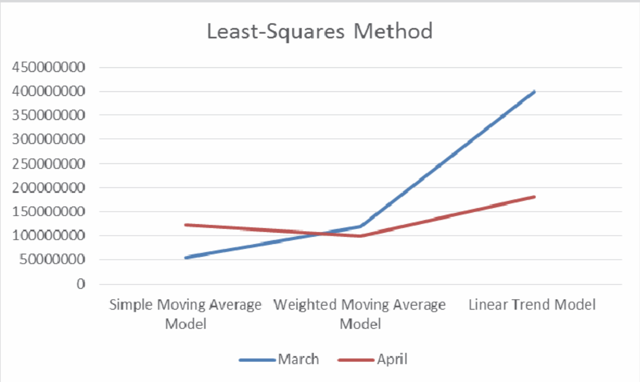

Figure 14. Least-squares method results

5. CONCLUSIONS

In this study firstly general information about demand forecasting is given. Definitions of qualitative and quantitative methods for sales forecasting are given and additionally, theoretical information about CPFR and data mining and warehousing is mentioned. In order to apply and compare the forecasting models, actual past sales data for seven different products (shirt, jeans, pants, women shirt, women jeans, women pants and skirt) are taken from a retailer in Turkey.

Before applying the forecasting models, the monthly sales data graphs are drawn and examined. Three different quantitative forecasting models, simple moving average model, weighted moving average model and linear trend model are applied by using the past sales data for forecasting March and April sales. The results are compared with the actual sales data. As a result of analysis it was seen that, the deviation from the forecasted values for women's jeans are minimum for all three methods. High deviation in forecasts obtained for pant model in March and shirt model in April when simple moving average model was selected. Weighed moving average model presented some errors in forecasting pants and women's pants (March) and shirt and women's shirt (April). Linear Trend Model gave quite big errors in forecasting shirt and women's pants models in March sales and women's shirt and women's pants models in April sales.

In conclusion, when forecasts were evaluated generally, it is seen that high correlation values were obtained between actual sales and forecasted sales values. Therefore it is concluded that these demand forecasting methods are very useful for the retail sector for accurate production and collection planning. The marketing departments can easily make analysis considering future demands for specific products, specific size groups, specific colors and even for the product groups with different price ranges by using these demand forecasting methods.

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