Mean-term Textile Sales Forecasting Using Families and Items Classification

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Abstract : Competition and globalization imply a very accurate production and sourcing management of the Textile-Apparel-Distribution network actors. A sales forecasting system is required to response to the versatile textile market and the need of the distributor. Nowadays, the existing forecasting models are generally unsuitable to the textile industry. We propose a forecasting system, which is composed of two models and perform forecasts on mean-term horizon for families and items sales. This system is based on classification procedures, authorizing the data aggregation. Performances of our models are then evaluated using the real data from a important French textile distributor.

Keywords : sales forecasting, textile distribution, classification.

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1. Introduction

Same as majority of industrial fields, the competitive environment of the Textile-Apparel-Distribution network implies to companies a rigorous management of their sourcing, production and distribution. The supply chain management (SCM) [1], includes all these processes from the expression of the needs until delivery of the finished products. This SCM concept uses tools which intervene at various steps and places of the logistic chain (GPA, MRP, DRP, ERP,...) and include different functions such as purchasing, sourcing, production planning, inventory control and exchanges of information. However, even if existing methods allow to improve reactivity of Textile-Apparel-Distribution network, many transformations, which are required to produce textile item, always impose significant and not very compressible manufacturing lead times. Globalization, which causes dispersion of network actors, also accentuates the increase of these deadlines. Thus, in order to deal with the customer's requests, companies often need to anticipate production and to stock up items. The main goal of the distributors is to offer the right product, at the right place and the right price, while maintaining the right stock (minimum stock). These constraints require an appropriate sales forecasting system. For the distributor, the correct anticipation of the consumer requests allows anticipating of the upstream companies to provision and adjust their production. Thus, the effectiveness of the supply chain optimization depends primarily on the precision of the sales forecasting [2][3].

The features of the textile market also complicates the forecast procedure. Indeed, the proposed system must be able to :

- deal with a large number of items references (about 15000 per year) and different aggregation levels of sales (figure 1)
- carry out mean-term forecasts (horizon of one season or year) to consider quantities to produce and plan the sourcing (figure 2),
- treat new items references (95 % of a collection),

- take into account many factors, called explanatory variables, which influence sales (weather and calendar data, marketing action, promotions, fashion, economic environment, ...),
- allow an easy intervention of decision makers.

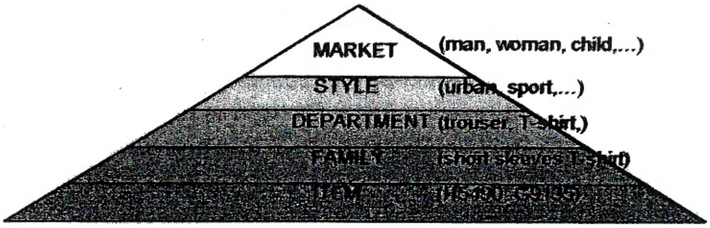

Figure 1. Example of Textile Items Aggregation

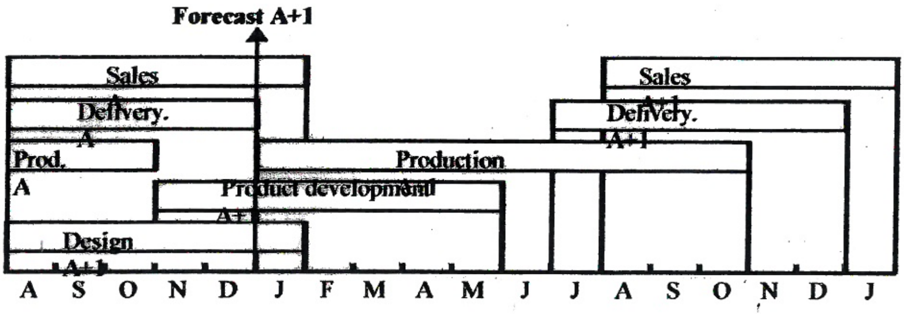

Figure 2. Planning of an Autumn-Winter Item Production

Forecasting is common in many fields such as finance, economy, meteorology, energy production, sociology... Amongst numerous existing models, we can group them into heuristic and statistical models [4]. The first ones are based on exploitation of opinions or intentions of people or experts group ; they are principally employed in marketing field. Statistical models exploit historical data. In this category are : moving average, exponential smoothing, SARIMAX model and its alternatives (ARMA, ARX, ...) usable with Box and Jenkins method [5][6][7], or traditional non-linear models (GARCH, SETAR, ...) [8][9]. Lots of software, which apply automatically these models, are available in the market (Walter's, Forecast Pro, Predicast, Autobox, Retek, ...). Lastly, it is possible to combine intuitive and quantitative methods, such as expert systems [10] or Bayesians models [11].

However, the performance of these traditional models depend strongly on the application field, the user experiment and the forecast horizon [12][13], which means that their effectiveness depends on the existence of reliable historical data to ensure a correct structure selection and an efficient adjustment of parameters. Most references generally include short historical sales data, which are influenced by neither controllable nor identifiable factors [14]. This suggest the need of new models to the detriment of the traditional models.

In fact, these last years, methods based on "soft computing" are largely developed for forecasting problem. In particular, neural networks has been exploited by many forecasters [15][16][17][18]. Although contribution of these models compared to the traditional ones seems mitigated in particular contexts [4][19][20], their capacity to model non-linear relations and their training and adaptation facility are very attractive for forecasting issue. Fuzzy inference systems, which are able to model human knowledge and can easily be interpreted, are also desirable in forecasting [21][22][23]: they are especially useful to quantify influence of explanatory variables on the time series [24]. Lastly, the combination of several "soft computing" techniques (neural networks, fuzzy logic and evolutionary algorithms) allows adaptive systems to learn complex relationships in uncertain environment [25][26].

In order to exploit the reduce historical data sales and to treat the numerous references, classification procedures have been applied. The effectiveness of classification for forecasting has been already validated [27][28] and particularly in textile sales [29][30].

Taking into account the very strong and specific constraints relating to the context, we chose soft computing techniques and classification procedures to implement our sales forecasting models.

In the following section, we propose the general principle of our system, which consists of two models performing forecasts in mean-term horizon and at two different sales aggregation levels (family and item).

The third section describes and evaluates our models with real data (3 years including about 42000 items organized in 322 families) supplied by an important French ready-to-wear distributor.

Lastly, the analysis of results concludes and suggests future prospects.

2. Proposed Forecasting System

In this section, we describe a sales forecasting system, which has been adapted to the textile apparel distribution network. This system is composed of two models and classification procedures (figure 3) which answer constraints of distributors (mean-term forecast on aggregate data by family and item) according to textile market features (influence of explanatory variables, seasonality, reduced historical data) [31].

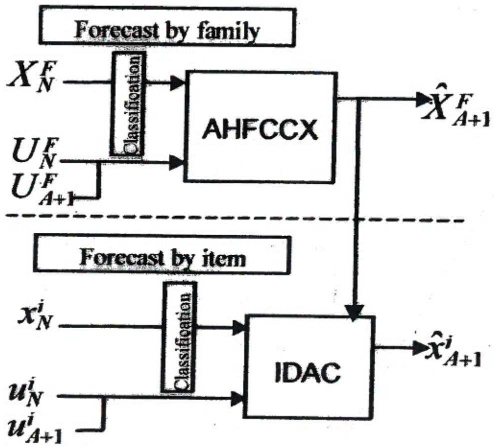

Figure 3: Global Forecasting System Principle

Notation

The main used notations are the following :

- p : period number (week) per season (or year)
- A : historical season number available
- X_N^F : historical sales data of season N for family F
- $\hat{X}_{A+1}^F$: mean term sales forecasting of season $A+1$ for family F
- U_N^F : considered explanatory variables of season N for family F
- x_N^i : item historical sales data of season N for item i
- $\hat{x}_{A+1}^i$: mean term item sales forecasting of season $A+1$ for item i
- u_N^i : considered descriptive criteria for items clustering of season N for item i

Family sales forecasting

In order to treat the sales seasonal behavior and the influence of explanatory variables, forecasting models need complete historical data of several years. To obtain such as historical textile data, the sales aggregation by items family is required.

3. Classification procedure of families

Historical data available in textile distributor are often very short (from 2 to 3 seasons maximum), despite of data aggregation by family [32].

Correlations between items sales and explanatory variables are often very complex. Influence of these variables is also very different according to the considered family, which requires a learning process of the model for each family.

However, fuzzy inference system training generally requires important time series [21]. Thus, in order to increase the training data number, a classification procedure is envisaged to aggregate families. The goal is to cluster families which have similar behavior face to explanatory variables. The learning process of the model is then performed, not on historical sales of each family, but on all historical family sales of a same cluster.

In order to differentiate the clusters, we have selected a hierarchical classification procedure. The chose classification criteria allows to characterize sales behavior according explanatory variables. Thus, items family having similar sales profiles are clustered together. In deed, sales profile, which is easily extract from historical sales, contains essential information about sales evolution. Though, it is possible to analyze the impact of a classification procedure according to others quantitative criteria (for example: correlation coefficients between sales and explanatory variables) or qualitative criteria (for example: marketing data). In order to determine the optimal cluster number, the Xie criterion is used : [33]:

$$Sxie = \frac{\sum_{k=1}^{c}\sum_{i=1}^{S} \mu_{ik} d^2(z_i, a_k)}{N \times d_{\min}^2}$$

with :

c	cluster number
S	family number
a_k	center of cluster k
z_i	family i
d_{min}	minimum distance between cluster centers
μ_{ik}	membership degree of family i to cluster k (μ_{ik}= 0 or 1 in hierarchical classification)

This criterion allows to obtain the best compromise between compactness, $d^2(z_i, a_k)$, and separability, $d_{\min}^2$, of clusters. The chose distance is the Euclidian distance.

4. Mean-Term Family Sales Forecasting: AHFCCX Model

In order to reduce the number of parameters to optimize, we have, for mean term horizon, chosen a family sales forecasting model based on separation of the seasonality and the explanatory variables treatment. This automatic model principle, called AHFCCX (Automatic Hybrid Forecasting model with Corrective Coefficient of eXplanatory variable influences), mainly consists (figure 4) in:

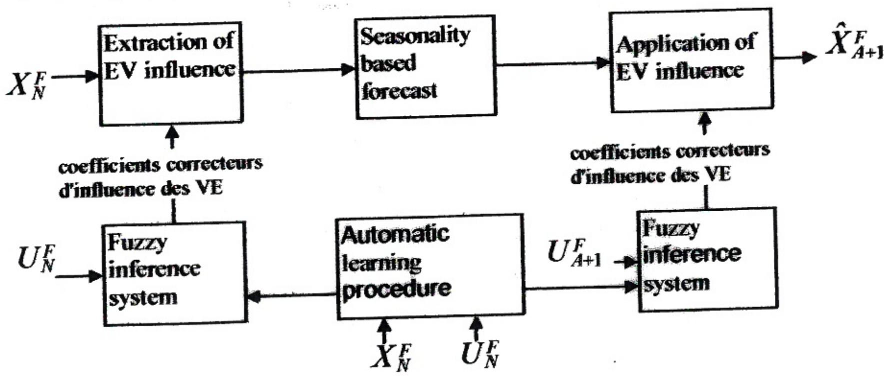

Figure 4: AHFCCX Model Principle

- extracting the considered influence of explanatory variables (EV) (price, data calendar) of the historical sales,
- applying a simple forecasting model based on sales seasonality and not taking into account the influence of explanatory variables,
- adding the influence of explanatory variables of the future season to forecasts previously obtained.

The major difficulty is to quantify the influence of explanatory variables. This problem can be solved by a Fuzzy Inference System (FIS) whose training procedure (founded on neuronal or genetic tools) exploits expert knowledge [34][35]. Indeed, the influence of some explanatory variables on the sales, such as promotions, is a quite vague concept, which can be treated efficiently by a fuzzy inference system [20].

However, taking into account of the large number of references (322 families), the expert intervention becomes unsuitable. The proposed AHFCCX model is based on an automatic learning of a Takagi-Sugeno FIS [36][37] from historical data. The structural (choice of the rules of inference) and parametric adjustments are assured by a genetic algorithm and a gradient based method respectively [32].

Item Sales Forecasting

The approach is different comparing to the family sales forecasting. Items references (i) are generally not renewed and have a very short lifetime (6 to 12 weeks) largely compared with the families sales periodicity (52 weeks). Correspondence between items (concept of "source" model), codified in alpha-numeric characters, is also often lost from one season to another. Generally, historical sales of future items data are not available. The only accessible historical data are the last seasons items sales of the considered item family (F). In this context, the use of time series forecasting models is unsuitable. However, the distributor can provide various criteria concerning future items such as life period, price, number of stores distributing the item, different number of colors, ... which will allow to consider an items classification.

4. Classification Procedure of Items

The proposed solution is based on an items classification of each family according to different criteria. The aim is to obtain clusters of items, which hold the same behavior in terms of sales. The main difficulty is the choice of significant and available criteria. According to experts, qualitative criteria like style, material,..., seem the most appropriate. However in our context, these data are rarely accessible [13]. The only knew criteria for new items are : period of sales, price, number of deal store and number of different color.

The classification procedure is based on hierarchical method [38][39] and composed of two phases: classification of historical items and attribution of new items to clusters.

The optimal cluster number is selected through the Xie criterion previously definied (section 2.2.1).

The applied distance is the Euclidean distance.

A life curve of each cluster is performed from the life curve of all historical items included in the corresponding cluster.

Each new item is attributed to the cluster whose the center is the nearest in term of Euclidean distance. The estimate life curve of a new item is then the life curve of his attributed cluster, adjusted to his sales period.

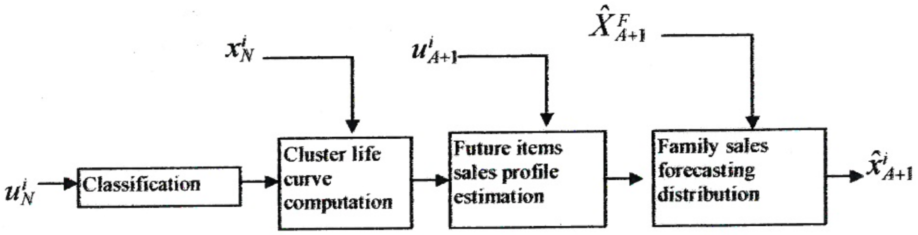

Figure 5: IDAC model principle

5. Mean Term Items Sales Forecasting : IDAC Model

The proposed model, called IDAC (Items forecasting model based on Distribution of Aggregated forecast and Classification) [40] estimates the items (i) sales of the same family (F) without requiring historical data. This model is based on the family sales forecasts distribution (computed by model AHFCCX) from the life curves achieved by the classification procedure.

The principle of model IDAC is as follows (figure 5):

- a partition $P(c)$, composed of c classes, is carried out from historical items sales data of the same family, similar according to descriptive criteria quoted previously,
- historical sales data belonging to the same cluster allow computation of a specific life curve,

- future items are associated with the cluster where the center is the most similar according to the criteria considered,
- estimated sale profiles of the future items are characterized by the life curve of their associated cluster and adapted to their life period,
- finally, from these specific profiles, the sales forecasting of each future item ($\hat{x}^i_{A+1}$) is defined by distributing the corresponding family forecasts ($\hat{X}^F_{A+1}$) according to the life curves (figure 6), and translated by the following relationship : $\hat{x}^i_{A+1}(t)=\dfrac{c_i.\hat{X}^F_{A+1}(t)}{c_i+c_k}$.

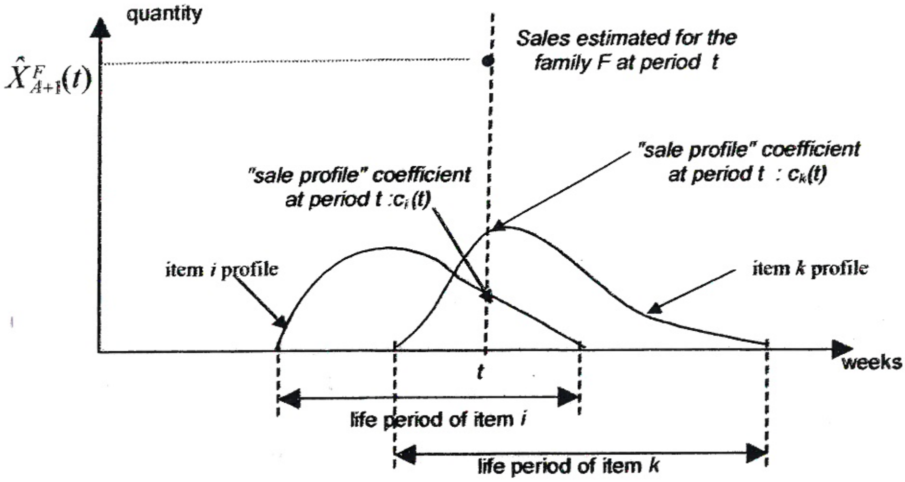

Figure 6: Example of Family Forecast Distribution on two Items

Experimentation

In this section, we validate the performance of our models with real database from the past three years (1998, 1999 and 2000), which is composed of 322 families and 42000 items from a large French textile distributor. The first two years are employed for the training of the models parameters and the third year evaluates the forecasts accuracy.

Traditional models for comparison

Mean-term families sales forecasting

These traditional models, tested on the mean-term families sales forecasting, are :

- Basic model (BMS)

Basic model BMS (Basic Model with Seasonnality), applied for the mean-term families sales forecasting, is founded on seasonal historical variations average.

- Holt Winter model with Seasonality (HWS)

This model, tested on the families sales at mean and short term, is based on the multiplicative seasonality principle. The optimization of parameters is carried out by the least squares method.

- Automatic models selection by the Forecast Pro software (AS-FP)

These models do not take into account of the explanatory variables and are applied for comparative families sales forecasting at mean and short term. The Forecast Pro software, in one hand, selects amongst 3 models (moving average, exponential smoothing, Box&Jenkin's), the most adapted to the series and on the other hand, optimizes its parameters. Various statistical tests are also carried out automatically to detect series stationary and the seasonality.

- ARMAX model

In order to experiment an additional model with explanatory variables, we also tested model ARMAX for mean and short term families sales forecasts. The parameters are optimized by a Gauss iterative Newton algorithm [41].

Mean-term items sales forecasting

- IDA model

This model [40] relies on the same sales forecasting distribution principle as IDAC model. The estimation of sales profile of future items results from the sales profile average of all historical items belonging to each family.

- Basic distribution model (RB)

The model RB, which authorizes new items without proper history treatment, uniformly distributes the family forecasts.

Accuracy criteria

In order to quantify the errors of tested models, we selected the following two criteria :

- $RMSE=\sqrt{\frac{1}{P}\sum_{t=1}^{P}e^2(t)}$ (Root Mean Square Error). This criterion strongly sanctions important forecasts errors. It is expressed in the same unit as the studied series. RMSE criterion or its alternative MSE (= $RMSE^2$), is frequently applied. However, its strong penalization of specific errors and its difficulty of comparing models on several series are particularly criticized [42][43][44][45]. Nevertheless, we apply this criterion for his development facility and interpretation and for its current use.
- *MdAPE* (Median Absolute Percentage Error) = median value of $APE_t=\left|\frac{e_{M,t}}{X_t}\right|$ classified by ascending order of the considered series. The *MdAPE* criterion, slightly sensitive to aberrant points, is recommended to compare models on numerous series [42].

Mean-term family sales forecasting

The performances of mean-term forecasting models BMS, AS-FP, HWS, ARMAX and AHFCCX are evaluated for 322 families (composed of 41966 items).

The optimal clusters number obtained with the Xie criterion on the 322 families is equal to eight. The learning process of the AHFCCX model is not carry out on the 104 weeks (2 years) of each family, but on all families included in each cluster. The training database size is thus significantly more important (table 1).

Table 1: Training Database Size of Each Cluster

Clusters	Number of families	Training database size (number of weeks)		
1	27	27 x 104	=	2808
2	20	20 x 104	=	2080
3	20	20 x 104	=	2080
4	40	40 x 104	=	4160
5	43	43 x 104	=	4472
6	97	97 x 104	=	10088
7	42	42 x 104	=	4368
8	33	33 x 104	=	3432

The treated explanatory variables by the AHFCCX mean-term automatic forecasting model were selected by some textile market experts in accordance to their significance but also to their availability in the database. Only the selling price per week and the holiday's periods were chosen.

AHFCCX model, which separately integrates sales seasonality and influence of explanatory variables, authorizes training of parameters on relatively limited historical data. The automatic procedure has many advantages for experimentation on many references. Thus, AHFCCX model, tested on the 322 families, significantly improves the accuracy criteria *RMSE* and *MdAPE* compared to employed traditional models (figure 7).

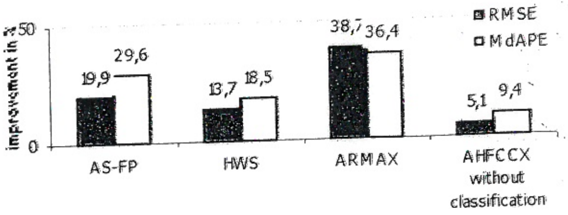

Figure 7: Improvements Completed by AHFCCX Model on 322 Families

Mean-term items sales forecasting

The three mean-term items sales forecasting models RB, IDA and IDAC are tested on the 4070 items sales resulting from families with most turnovers sales.

The applied criteria for items classification of IDAC model are average price and number of stores distributing the item. The choice of criteria is justified by their influence on the sales and their availability. The envisaged classification procedure is a hierarchical ascending type.

The IDAC model classification procedure generates, for a same family, clusters quite distinctive according to item price and number of stores distributing the item (figure 8). Thus, we can hope that the estimated sale profile of each cluster is more accurate than the average profile computed (IDA model) for all items included in the same family (figure 9). However, results are sometimes ambiguous. In fact, the IDAC forecasting model is often more accurate than RB and IDA models, in particular the estimation of the items sale profile (figure 10); however, a deficient sales quantity forecast of some items is strongly sanctioned by *RMSE* criterion. Thus, the RB model obtains the best performance in term of *RMSE*, compared with IDAC model (figure 11).

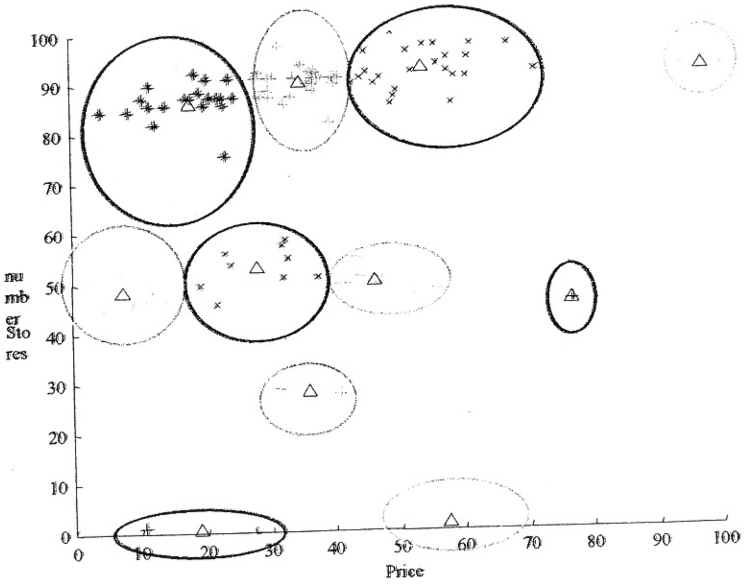

Figure 8: 11 Clusters resulting from Women T-Shirt Classification

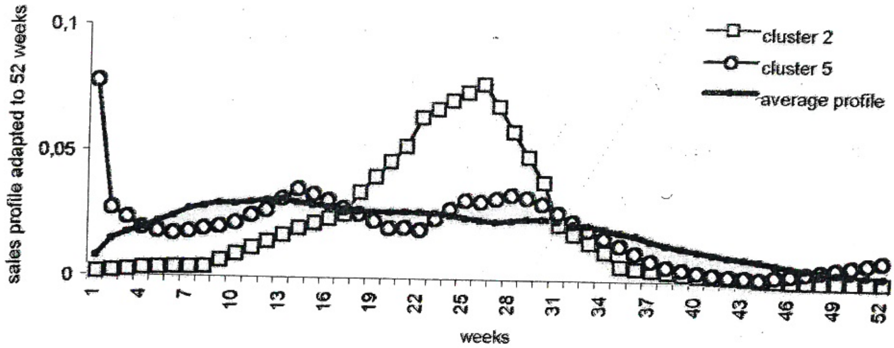

Figure 9: Example of Center Life Curve and Average Profile

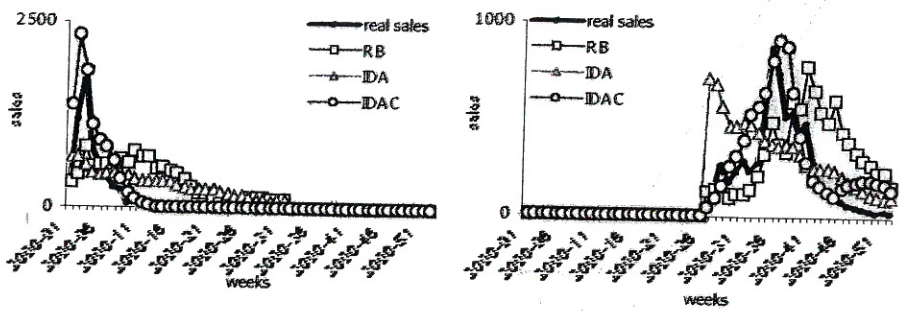

Figure 10: Examples of RB, IDA and IDAC Models Forecasts

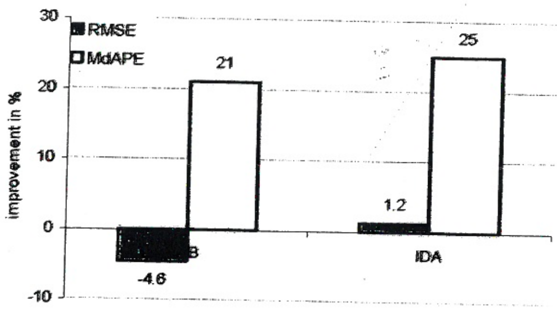

Figure 11: Improvements Completed by IDAC Model on 4070 Items

5. Conclusion and Prospects

From real data provided by a major textile distributor, we have applied our global system which is composed of various forecasting models. These last ones deals with sales forecasting aggregated at two different levels, for mean and short term horizons. The use of real data allows to take into account the strong constraints of textile industry.

The mean-term family sales forecasting performed by a model, based on a fuzzy inference system (AHFCCX model), integrates separately and automatically the sales seasonality and the influence of explanatory variables.

The principle of the IDAC model, which achieves the mean-term items sales forecasting, relies on the family forecasts distribution of the corresponding items and on the life curve estimation from a classification procedure. As the items references are generally not renewed from one season to another, the principal difficulty for this model remains in the impossibility of exploiting the historical sales of future items.

However, our experimental results can sometimes be refined and lead us to consider future developments which correspond to the following progress axes :

- to take into account of more effectively the influence of explanatory variables on family sales (new selection of inference rules),
- to determine more accurately amounts of items sales, by using a classification procedure which includes qualitative parameters of the products (style, raw material,...) when the information is available,
- to compute sales forecasting by color and size,
- to readjust the mean-term forecast from the last load sales (short forecast : horizon one to three weeks) in order to replant the sourcing.

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