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AN AUTOMATIC TEXTILE SALES FORECAST USING FUZZY TREATMENT OF EXPLANATORY VARIABLES

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ABSTRACT

To reduce their stocks and to limit ruptures, textile companies must improve their supply chain management. This organization requires sales forecasting systems adapted to the uncertain environment of the textile field. The uncertainty is characterized by noisy data, short historic and numerous explanatory variables that influence the sales behavior. This paper deals with new forecasting models based on "soft computing" and more particularly, last evolutions of hybrid fuzzy model (HFCCX) developed in previous works. HFCCX model uses fuzzy logic abilities to map the non-linear influences of explanatory variables to perform mean-term forecasting. The drawback of this model is the require of an expert judgment for the learning process. The last improvements of our model called AHFCCX allow an automatic learning of the explanatory variables influence. To evaluate performances, a comparative test between AHFCCX, HFCCX and classical models has been applied to real data of textile items selected from an important French ready-to-wear distributor.

KEYWORDS : Textile-apparel industry, Sales forecasting, Fuzzy inference system, Automatic learning, Explanatory variables.

1. Introduction

To set up all logistic steps require to produce and deal a product, textile managers must rely on efficient and accurate forecasting systems. A suitable sales forecast, allowing to predict in due time the sufficient quantity to produce, is one of the most important factors for the success of a lean production (Kincade, 1993). Forecasting is an essential planning tool for decision making process (Geriner, 1991) (Lee, 1995). All the Supply Chain Management optimization depends on the forecast quality of the finished products sales (Sboui, 2001) (Graves, 1998).

That supposes to take into account as much information adapted to the forecast context as possible. To summarize, a such a textile sales forecasting system require :

- to quickly react to a significant variation of trend and seasonality,

- to identify and to smooth purely random events,
- to perform forecasting on short historic sales data,
- to take into account the influences of explanatory variables (Figure 2).

Different forecasting methods exist (Mastorocostas, 2001): linear/non-linear, adaptive or not, explanatory or extrapolative as exponential smoothing models (ex: Holt-Winters), Box-Jenkins model with autoregressive integrated moving average (ARIMA) processes, dynamic regression models with explanatory variables, econometric methods (Bourbonnais, 1992)(Wheelwright, 1985), and more recently, artificial neural network (ANN) (Patterson, 1996) or fuzzy logic (Kim, 1997) based models.

The major drawback of this methods is that almost all applications are quite specific and have to use generally a combination of several forecasting models (Bourbonnais, 1992) (Kim, 1997). Another difficulty, particularly existing in the textile-apparel industrial network, consists of achieving forecasts in uncertain environment. All events, which are able to influence the forecasting system, are neither strictly controlled nor identified (De Toni, 2000). Besides, the important parameters number some models complicates the learning on short historic.

After reminding the background of the distribution management in the textile-apparel industry, and the formalization of the forecast issue, we keep in mind the features of the HFCCX model carried out in previous work (Thomassey, 2001). Then, we propose an improvement of the HFCCX model, which achieves a automatic learning of the explanatory variables influence. The aim is to show the ability of fuzzy inference systems to learn on short historic without human intervention. Thus, the model could be used for a large items number (up to 15000 for textile distributor). Fuzzy logic is very interesting to model human knowledge (Shimojima, 1995)(Zadeh, 1994)(Van Lith, 2000) and it is tolerant with respect to the noisy data (Van Lith, 2000). Automatic methods are preferable when the number of series is significant (Geriner, 1991). In addition, with a strong explanatory variables influence, a manual model tune could be more delicate (Geriner, 1991). The models structure and the learning procedure are adapted to short and noisy time series, as well as a mean-term prediction horizon. A selection of some well known classical allows to evaluate the performance of our model in a comparative test. This comparative test is achieved with real data of basic textile items, proceeding from a French representative ready-to-wear firm. Finally, after comments and conclusion on the results, extensions to the models are suggested.

2. Background

The choice of the forecasting model depends on the uncertain environment of the textile apparel field. So, it seems important to remind the prediction context. Then, the general features of the forecasting system are introduced.

2.1 Textile background

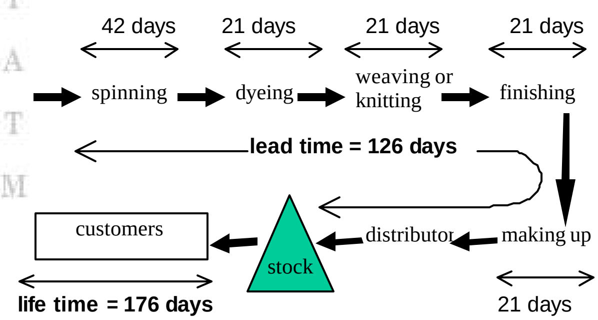

Figure 1. Lead time of the textile apparel distribution operative chain from fiber to customers.

2.1.1 Forecasting purpose.

The production flow forwards by a network of firms. The firms represent manufacturing stages and induce proper intermediate inventories. To avoid being out of stock or over-stock, synchronization the entire network is required. Unfortunately, the products are too various and the global lead-time (or flow time) is too long to allow appropriated production reactivity. In deed, a study of the "Institut Français du Textile et de l'Habillement" (IFTH) shows that the item life time is very short (in average 175 days) whereas the lead time is relatively long (in average 126 days) (figure 2). A solution is to introduce a strategic stock, adequately placed on the operative chain, in accordance with the delivery time imposed by customers (in stores) (figure 1).

2.1.2 Sale factors.

The textile field is probably one of the unstable markets. The short life cycle of textile items implies available sales data are reduced. They are also disturbed, considering the numerous influences of some factors controlled or not (Vroman, 2000).

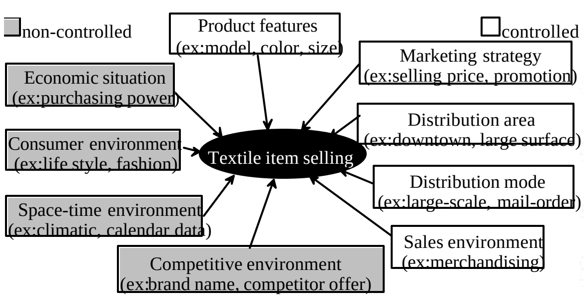

Figure 2. Main categories of explanatory variables.

The figure 2 presents the main categories of the variables that possess a significant influence on the textile items selling.

Some of these variables act on store frequentation, others on costumers purchase decision.

After the enumeration of these explicative variables, some remarks can be noted:

- the explanatory (i.e. endogenous and exogenous) variables list, for a data series, can not be exhaustive ;
- the interdependence of these variables complicates the study ;
- all the explanatory variables which influence the studied series, are not always available (example: incomplete promotions historic, competitors sales, …);
- finally, one of the greatest difficulties is the acquisition and the interpretation of reliable data (e.g.: historic of the items sales with opening and closing of distribution centers not recorded) and coherent (e.g.: day climatic data with monthly sales historic).

2.1.3 Forecasting data features.

One particularity for the textile sales analysis is the wide range of products and the significant number of item references. Then, a first preprocessing of data like clustering is imperative (Boussu, 1996). The difficulty is to choose the aggregation level (figure 3) of the sales forecasts. These levels are determined from the use profile and the manufacturing features of the textile product. This choice must allow the treatment of the explanatory variables influence. In deed, more the aggregation level is high, more the interdependencies between endogenous and exogenous variables imply difficulties to model the sales. The models application in this paper is achieved with sales data classified by model.

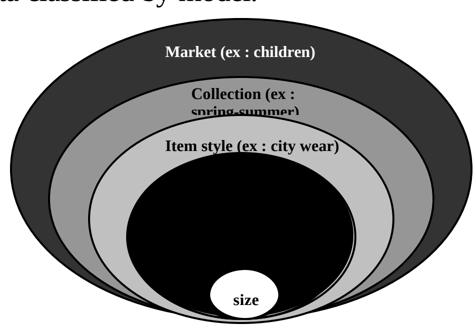

Figure 3. Aggregation level of textile items.

The forecasting horizon required by users appears also to be a textile sales characteristic. Figure 4 presents the production planning of autumn-winter textile items, from creation to distribution in textile warehouse. It shows that purchasing managers need to know almost one year before the raw materials quantities to order, which correspond to the forecast total quantity of each textile product range.

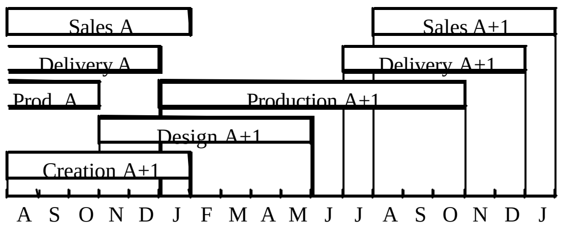

Figure 4. Production planning of autumn-winter textile items.

In this paper, we focus on the mean-term forecast (one season or year), i.e. to return an estimation of the sold quantities and the sales shape, during the entire season.

The forecasting period commonly used by marketing managers in textile distribution is week. It practically corresponds to the rhythm of purchasing for consumers.

2.2 Problem formalization.

As explained previously, the forecasting model must estimate the sales for season A+1 (figure 4), from the historic sales data until season A, the explanatory variables assigned to the same period, and the explanatory variables known for next season A+1. The explanatory variables used are quantitative indicators.

The general form of the prediction model is then:

$$\hat{X}_{A+1}^{p} = F(X_N^p, U_N^{n,p}, U_{A+1}^{n,p}) = X_{A+1}^{p} + e_{A+1}^{p}$$

$N \in [1,A]$ with $U_N^{n,p} = \begin{bmatrix} u_{N,1}^1 & \cdots & u_{N,p}^1 \\ \vdots & \ddots & \vdots \\ u_{N,1}^n & \cdots & u_{N,p}^n \end{bmatrix}$,

$X_N^p = [x_{N,1}, ..., x_{N,p}]$ and $e_{A+1}^p = [e_{A+1,1}, ..., e_{A+1,p}]$

where :

- p the number of periods a season;
- $x_{N,t}$ the real sales value for season N at period t;
- $u_{N,t}^n$ the value of the n^{th} explanatory variable for season N at period t;
- $\hat{X}_{A+1}^p$ a p-row vector of sales estimation for season A+1 from period 1 to p;
- X_N^p represents a p-row vector of real sales data known for the season N, from period 1 to p;
- $U_N^{n,p}$ a nxp-matrix of the p values of the n explanatory variables for season N;
- F a nonlinear function: $R^{p[A.(n+1)+n]} \rightarrow R^p$;
- e_t the prediction error at period t ($e_t = \hat{x}_t - x_t$).

This paper has been focused on the ability of fuzzy theory to allow the use of interpretable rules by the user and to characterize the non linear influence of input explanatory variables, even in an uncertain environment (Kuo, 1998). It is also acquired that fuzzy inference systems, through the current optimization methods, can learn as well as neural networks (Bersini, 1992).

3. AHFCCX forecasting model

The HNCCX (Vroman, 2000) and HFCCX (Thomassey, 2001), developed in precedent works, models are an alternative to the forecasting problem enounced previously. The AHFCCX model presented in this study is a HFCCX based model, which does not require an expert intervention for his learning. Automatic models building for univariable series has been show to produce results comparable to an expert or manual analysis (Hill, 1980)(Poulos, 1987). Our model applies to multivariable series in a very disturbed context. First, the general form of the HFCCX model is remind. Second, AHFCCX learning procedure is summarized and features are presented by focusing on differences with HFCCX model.

3.1 Recall: HFCCX model characteristics.

The HFCCX model is a Hybrid forecasting model with Fuzzy estimation of Corrective Coefficients of the eXplanatory variables influence. This model allows the treatment of the influence of the explanatory variables with structure-limited fuzzy estimators; consequently that permits a correct learning even with short historic. Furthermore, the model learning is based on the marketing managers in textile distribution knowledge. However, when the model is applied on numerous items, this last characteristic becomes very fastidious, and so the expert intervention is a drawback.

The prediction process is divided into three stages:

- sales data are deseasonalized from the influences of explanatory variables,
- resulting data are used to predict the sales of the next season, with seasonality-based forecasting method,
- sales forecasting are reseasonalized with the influence of explanatory variables corresponding to the next season.

The general form of the model is shown on figure 5.

The MH function converts the original sales data to deseasonnalized ones X'^{p}_{A}, from the corrective coefficients CS^{p}_{N} estimated by the MCS function.

The MCS function estimates the influence of explanatory variables (quantitative indicators) and changes them into corrective coefficients of seasonality CS^{p}_{N}.

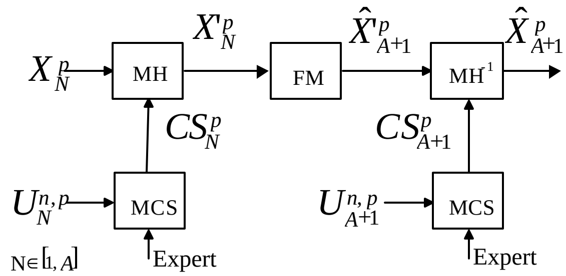

Figure 5. General form of the HFCCX forecasting model.

The feature of the HFCCX model has been introduced in precedent works (Thomassey, 2001). The Fuzzy Inference System (FIS) used for this MCS function is a Takagi - Sugeno FIS (Takagi, 1985). This model has the advantage of applying with more facility the techniques of training and optimization (Van Lith, 2000) than the model of the Mamdani type.

The FM function predicts the sales on season A+1 from the deseasonalized sales data known until season A. The method used is one of the simplest forecasting methods: the seasonality average. Only the seasonality forecast was studied here, the total quantity sold being for our distributor partner less problematic. This basic method was selected in order to show the significant influence of the explanatory variables treatment on the forecast improvement. Besides, its low parameters numbers does not require an adjustment as for other classical models.

The obtained predicting data $\hat{X}'^{p}_{A+1}$ are reseasonalized thanks to the inverse function of MH : MH^{-1}.

The coefficients CS^{p}_{A+1} required by MH^{-1} are simulated with the same MCS function, learned previously on seasons 1,…,A, from the explanatory variables U^{n}_{A+1} of season A+1.

3.2 AHFCCX model.

The AHFCCX (Automatic HFCCX) is a HFCCX based model, i.e. his concept is to realize a forecast on series which are explanatory variables influence free as explain in section 3.1. To help understanding, the process is divided in two phases: the training (or learning) and the simulation (figure 6). As any expert intervention is required, thus this model can be used on a large items reference number.

3.2.1 Learning procedure

The choice of the optimization method depends on the parameters type to be optimized. Indeed, three parameters kinds can be trained in a fuzzy system: input membership, output membership and structure learning. Each category of parameters can be treated by a particular method (Pokorny, 1997): neural networks with back-propagation method (Bersini, 1992) (Hartini, 1996) (Wu, 1999), genetic algorithms (Hartini, 1996) (Shimojima, 1995) (Van Lith, 2000) (Klir, 1995)…

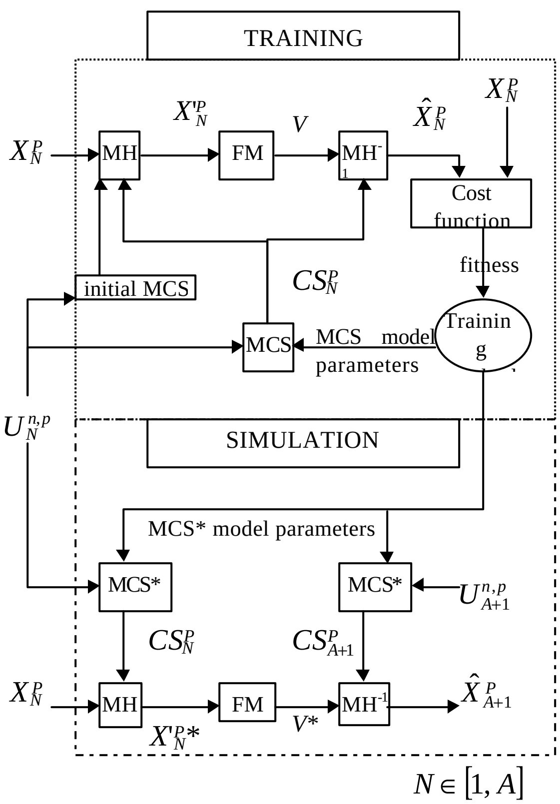

Figure 6. AHFCCX model.

The learning procedure of the MCS function uses same method as with the HFCCX model. It is carried out in the following way: output memberships functions of the default rules set are tuned with a Levenberg-Marquardt based method (Levenberg, 1944)(Marquardt, 1963)(Moré, 1977), and then, a genetic algorithm selects rules set which allows a better precision. Inputs membership functions tuning is time consuming and not affect in a significant degree the results; contrary to the preceding output memberships functions parameters, these ones are easily adjustable by an expert. In the training process of the HFCCX model, optimization of the membership functions are carried out for each chromosome of each generation of the algorithm genetic. This method is very time consuming. That's why, for the AHFCCX, this optimization is realized only one time on the initial rules set. Let remember that AHFCCX model is destined to be use on a large items number.

The rules selection by the algorithm genetic allows an easier rules interpretation and deletes rules that damage system performance (Zadeh, 1996). The model structure must also be the smallest as possible in order to avoid the overfitting problems (Fiordaliso, 1998). Thus, in order to perform a selection comparable to a neural networks pruning, the number of parameters is penalized in the fitness function. Therefore, the evaluation of the fitness function is proportional to the criterion RMSE + C x SBIC, where RMSE is Root Mean Square Error criterion (see section 4.1), C is a constant whose value are function of data used and SBIC is the Scharw's Bayesian Information Criterion (see section 4.1). RMSE criterion penalizes prediction deviations and SBIC criterion penalizes number of rules. Then, the fitness function allows improving the accuracy (through the RMSE criterion) with a minimal rules set (through the SBIC criterion).

3.2.2 Main evolutions between AHFCCX and HFCCX models.

In his process, the HFCCX model requires that an expert quantifies the explanatory variables influence. This intervention allows carrying out a sales curve independent of explanatory variables. The learning procedure goal is to minimize a cost function proportional to the variations between the expert curve and the HFCCX model curve ({ X'^{p}_{N} } series) (figure 5). With the AHFCCX model, the expert intervention is removed. The model performs directly a "life curve", called V in figure 6, of the item from the historic data. This curve relates to the sales without explanatory variables influence. From this one, the model computes the forecasting on the historic seasons ($\hat{X}^{p}_{N}$) by applying explanatory variables influence. It is only at this stage that the accuracy is evaluated by the cost function compared to real sales. The V "life curve" is the average of the seasonality of historic seasons free of explanatory variables influence.

$$V = \left[V_1, ..., V_t, ..., V_p\right]$$

$$V_t = \frac{\sum_{J=1}^{A} s_{J,t}}{A} \quad \text{with} \quad s_{J,t} = \frac{x'_{J,t}}{\sum_{i=1}^{p} x'_{J,i}}$$

where $\left[x'_{J,1}, ..., x'_{J,p}\right] = X'^{p}_{J}$ the deseasonnalized sales from the corrective coefficient estimated by the MCS function.

The learning minimizes the cost function and gives the optimum parameters of the MCS model called MCS* (figure 6). $X'^{p}_{N}*$ and V* are respectively the historic sales independent of explanatory variables influence and “life curve” resulting from MCS*. It is from this last one than influence of the explanatory variables of simulation period (*A+1*), computed by MCS* model, is applied to estimate the final forecast.

4. Experimentation and results.

In this section, the AHFCCX model proposed previously is tested on real textile items sales of a distributor. First, criteria use for evaluation are remained. Next, sales and explanatory data employed are presented. Then, some representative classical models are selected for the comparison with our model. Finally, the AHFCCX model performances are examined and compared to these others models.

4.1 Prediction performance evaluation

In time series identification and forecasting, a usual criterion of the models accuracy is the root mean square error (RMSE). Given the p-dimension, test set is evaluated on the forecasting season A+1. This criterion is then:

$$RMSE_{A+1} = \sqrt{\frac{1}{p}\sum_{t=1}^{t=p}\left(x_{A+1,t} - \hat{x}_{A+1,t}\right)^2}$$

Such criterion penalizes important prediction deviations (Bourbonnais, 1992).

However, it is also necessary to penalize the parameters number m of the modeling function, according to the aim of generalization. Thus, to measure the models quality, we use the Scharw's Bayesian Information Criterion (SBIC) (Bourbonnais, 1992). As previously, the smaller is the criterion, the better is the quality model. It is expressed by the following relation :

$$SBIC_{A+1} = p.\ln\left(RMSE_{A+1}{}^2\right) + m.\ln(p)$$

with p the number of data considered and m the parameters number of the model.

4.2 Sales data and explanatory variables.

4.2.1 Sales data.

Sales forecasting data acquisition and choice in textile distribution are real problems. Sales data, especially in textile, are not always available and stored with the aggregation level required. Besides, it is comprehensible that textile distributors do not always agree to provide theirs sales data.

To achieve the comparative test, we chose two basic textile items, the first one is a pullover and the second is a trouser, sold during a complete season period. According to the aggregation levels shown on figure 3, these textile items can be categorized as autumn-winter and man city wear items. The chosen items family and model are quantitatively renown to be representative for distributors. Each data series is composed with 22 periods (from week 31 to 52) a season, during 3 seasons (from 1994 to 1996 for pullover and from 1996 to 1998 for trouser), including 2 years for the learning. The training data set is composed of two seasons (1994-95 for pullover and 1996-97 for trouser) and simulation data set consists of one season (1996 for pullover and 1998 for trouser).

4.2.2 Explanatory variables.

The input space is build from explanatory series that influence the sales. The explanatory chosen variables are also considered to be significant, according to marketing managers. Figure 7 shows the three used variables, which are based on the selling price, the holidays period, and the season sequences. The price is a very significant argument in the purchase decision of the customer and the holidays are generally responsible for a stores frequentation rise. To complete the holidays period, the variable based on season sequences is considered.

To introduce these explanatory variables in the input space of the forecasting models, rough data are modified in indicators continuous and normalized.

- Selling price. The possessed values correspond to the percentage of stores that practice a decrease of price. The used variable is a price indicator proportional to this possessed value.
- Holidays period. The holidays indicator represents the number of the country areas in holidays time. Another indicator build on holidays periods is the holidays –1 indicator that is the holidays indicator of the previous week.

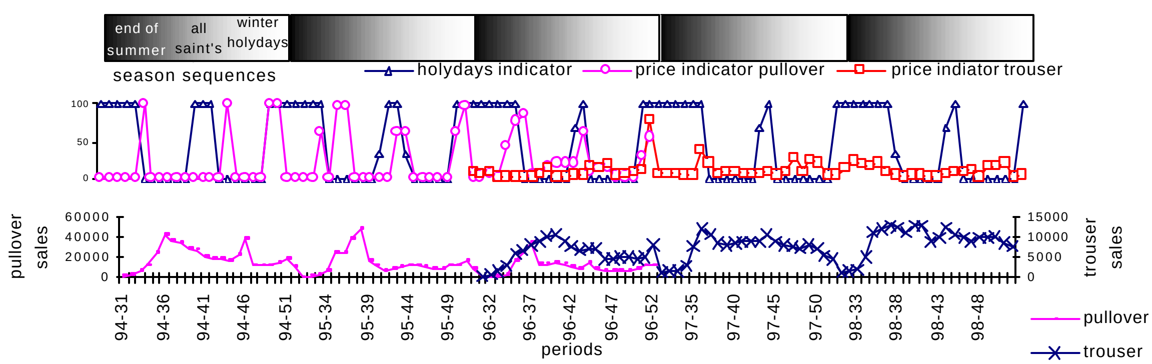

Figure 7. Input indicators (price, season, and holidays) and total sales of the two items

Table 1. Features of the choose models for comparison

Forecasting model	Abbreviation	seasonal model	explanatory variables	learning methods	Parameters	number of parameters	judgmental or expert intervention
Holt-Winter with Seasonality	HWS	yes	no	Gauss Newton based	a, b, g (**)	3	-
Box & Jenkins	BJ	no	yes	Gauss Newton based	q, r (***) v, w (****)	$q + r + v + w$	possible choice of model order
Forecast Pro - Dynamic Regression with eXplanatory variables	DRX-FP	no	yes	Newton based	Regressors	number of regressors	regressor choice (advised by the software)
Hybrid forecasting models Fuzzy estimation of Corrective Coefficients of the eXplanatory variables influence	HFCCX	yes	yes	LM – GA (*)	c_i (*****)	number of selected rules	Intuitive expert correction of explanatory variables influence
Automatic Hybrid forecasting models Fuzzy estimation of Corrective Coefficients of the eXplanatory variables influence	AHFCCX	yes	yes	LM – GA (*)	c_i (*****)	number of selected rules	-

(*) Levenberg-Marquardt based method for optimization of membership functions and genetic algorithm for rules selection (see 3.2.1)
(**) average, trend and season coefficients - (***) orders of the AR operator - (****) orders of explanatory variables operator
(*****) output membership functions (singleton)

- Seasons sequence. This indicator separates three distinguished sequences in the autumn-winter season. They represent the beginning of term, after the summer holidays (school return), the All Saints' Day period, and the proximity of the winter holiday (figure 7).

4.3 Classical models for comparison.

Table 2. Selected ruled and corresponding corrective coefficient for trouser

Indicators				Output
Price	Holidays	Holidays –1	Season	mf
Promotion	*School*	*School*	*All Saint's Day*	-0,61
Promotion	*School*	*School*	*Christmas*	-0,41
Promotion	*Holidays*	*School*	*All Saint's Day*	-0,30
Promotion	*Holidays*	*Holidays*	*School return*	-0,41
Promotion	*Holidays*	*Holidays*	*Christmas*	-0,30

Table 3. RMSE criterion on pullover and trouser.

	AHFCCX	HFCCX	HWS	BJ	DRX-FP
pullover	2723	2935	4699	3386	5415
trouser	1186	1151	2842	3029	2434

Table 4. SBIC criterion on pullover and trouser.

	AHFCCX	HFCCX	HWS	BJ	DRX-FP
pullover	391	382	381	453	397
trouser	327	338	359	374	365

For our comparisons test, we chose (table 1): the Holt-Winters model with multiplicative seasonality (HWS) (Bourbonnais, 1992), the ARX (AutoRegressive with eXplanatory variables) model linked to the well knows Box-Jenkins (BJ) procedures (Box, 1969) (Bourbonnais, 1992), and a dynamic regression models used by the professional software Forecast Pro (the selected regressors are explanatory variables and variables advised by the software). The two last models include explanatory variables. This condition is imperative to characterize the non-linearity of the structure. In many examples, explanatory variables increase the forecast accuracy (Geriner, 1991).

4.4 AHFCCX model results.

One of the fuzzy inference system advantages is the use of linguistic rules, which can be interpreted. Thus, after the learning process, it is possible to observe how the system performs its computations. Table 2 shows selected rules by the genetic algorithm and corresponding corrective coefficients (which are output membership functions (mf)) after the learning procedure on trouser sales.

It appears that selected rules consider the price decreases (i.e. price indicator = *promotion*). Thus, as intuitively expected, the selection method judges this factor influent. Generally, selected rules are coherent with expert knowledge.

4.5 Comparison.

This comparison test is achieved on pullover and trouser sales of the third season presented in previous section according to the following criteria: the RMSE and SBIC criteria (tables 3 and 4). Figure 8, obtained with the sales of considered items, illustrates graphically the main performances of each forecasting model.

As envisaged, the short histories do not allow classical models to learn in an optimal way series characteristic. The learning processes of these models need more input data for statistical validation. The dynamic regression model gives bad result on pullover sales. This model do not anticipate correctly "sales peaks" in the end of summer holidays and Christmas periods. Despite of this, his accuracy on trouser sales is the best of classical model. Although BJ model presents better results of the classical ones for pullover data, these forecasts remain extremely disturbed.

The HW model does not take into account explanatory variables, but introduces the seasonality factor. Even if numerous factors are difficult to evaluate, particularly because of their interdependence, seasonality appears to be one of the most important, according to the structure of the data series. However, figure 8 illustrates, that for pullover, the HWS model, which not considers explanatory variables is undesirable in our context. Indeed, this model, which takes into account only history sales, cannot expect the change of "sales peak" due to different holidays periods or price fall. In contrast, the HWS model outperforms BJ model on trouser sales. These ones are strongly disturbed; consequently complex statistical models are unable to tune correctly their parameters and structure.

Figure 8 reveals the models capacity to map the explanatory variables influence. In particular for pullover, at the end of the summer holiday, AHFCCX and HFCCX models anticipate a better reply to the sales increase than the others. In the period 1996-44, the sales have sensibly improved, at a delayed period, in regard with the previous season. This improvement should correspond to the combined influence of the decrease of price, during the holiday at the All Saints' Day period.

In this period, HWS model has forecasted a "peak" with two weeks late. HFCCX model carries out here the best predict. Even if similar conclusions are more difficult to draw with trouser sales, however, it appears AHFCCX and HFCCX models perform a quite fine forecast in regards of others models.

These remarks prove the feature of fuzzy inference system to map nonlinear relations between inputs and output. It also relates the limits of seasonal-based models, like HWS model that strictly learns the past.

The main fact is that HFCCX and AHFCCX models realize comparable forecasts (tables 3 and 4). Not only AHFCCX model gives globally the best results of the comparative test, but in addition his automatic learning process is as powerful as a process with an expert intervention. However, two drawbacks have to be underlined. The first one is common to the HFCCX and AHFCCX models : the rules selection is significant and remains delicate. The genetic algorithm selection requires a certain experiment of the operator in order to tune the different parameters (population size, probability of mutation and crossover,…). The second one is that time consuming by the AHFCCX learning process still very significant. The main factor is the important time requires by the genetic algorithm, which selects fuzzy inference rules. This problem becomes very perturbing for a numerous references processing.

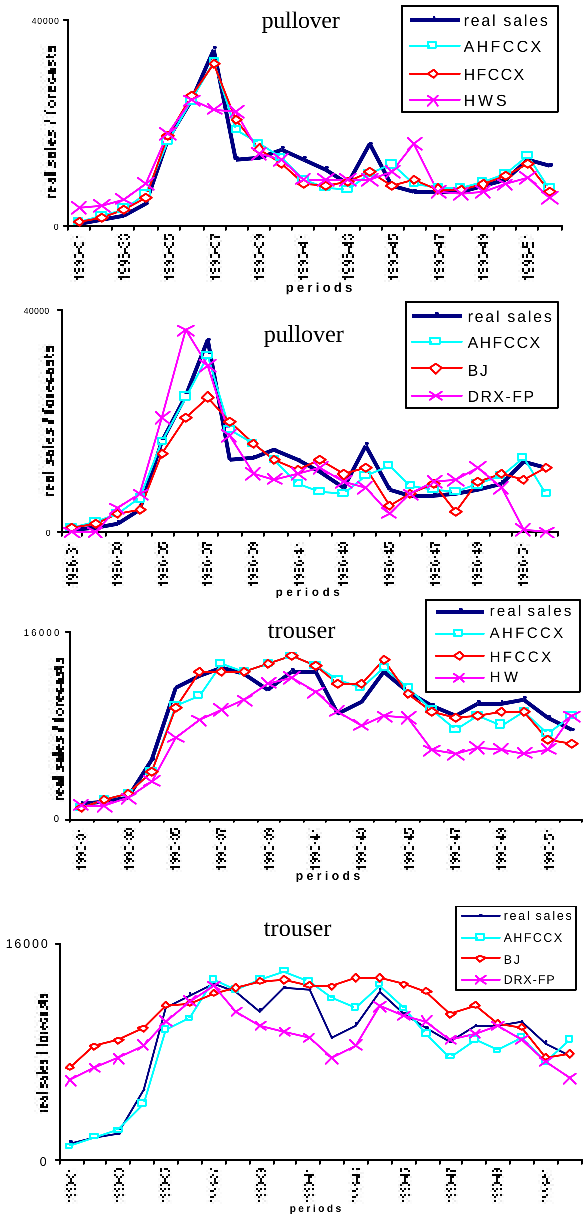

Figure 8. Comparison between forecasting models

In consequence, it can be envisaged to use only the output membership function tune and not to carry out rules selection to reduce the calculating time. The risk is then to decrease the model accuracy and to be exposed to the overfitting problem. Another solution is to select rules with a different method like example the Abe method (Abe, 1995).

5. Conclusion

In this paper, AHFCCX model confirms the advantages brought by tools like fuzzy logic to perform forecasting in the particular textile context, i.e. on short time series, in a mean-term horizon, and with explanatory variables under uncertain environment. Our new model have been compared on two representative winters textile items, with its predecessor, the HFCCX model, and some classical models: the Holt-Winters with seasonality model (HWS), a Box&Jenkins method (BJ), a dynamic regression model (DRX-FP) experimented on the renowned professional software Forecast Pro ©. Due to the lack of data, the comparison has not been enlarged on the more significant number of textile items family. However, the two articles choose are typical and basic according to our distributor partner.

Because essentially of the short series and the uncertain environment, the BJ and DRX-FP models give relatively good results, but they are unable to fit correctly their parameters. Without the introduction of explanatory variables, the HWS model, provides quite respectable results due to his relatively simplicity. Nevertheless, the only way to improve these results is to consider the influence of endogenous and exogenous factors. The best results are obtained with the AHFCCX and HFCCX models, due to the ability of fuzzy logic to translate the nonlinear relationship between inputs and output data. Despite these results, a negative aspect of the last models is the rules selection. Besides, for AHFCCX model the processing time, which is too significant for a generalization on all the distributor items range. However, this last model does not require an expert correction of the influence of explanatory variables for the learning stage. Indeed, with a human correction, the generalization on a large items numbers seems impossible. Besides, the intervention relevance can change from one expert to another.

Some possible developments of the model consist on the improvement of the learning procedures. An automatic learning of the explanatory variables influence is essential for an industrial development, but the processing time must remain acceptable. The idea is then either not to carry out the rules selection, either to use an alternative to the current method, which is genetic algorithm based. A compromise must be found between desired accuracy and processing time. Then, a simulation on a large data number must be performed. These evolutions will be the object of future works.

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