WORKLOAD FORECAST ALGORITHM OPTIMIZATION FOR RE-ORGANIZING RETAIL NETWORK

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ABSTRACT

This research is focused on developing an innovative approach for optimizing workload forecast algorithms in point of sale for retailers; this paper proposes a real case as validation framework and the procedures for optimizing and fine tuning the predictive algorithms for improving their performances. The analysis is based on different time series (i.e. sales, customers, working hours, etc.) correlated by the predictive algorithms. The paper proposes a metrics devoted to measure the performances considering the multivariable framework and the different target functions.

Keywords: forecast algorithm optimization, retail network re-organization

1. INTRODUCTION

Forecasting Models are used commonly to foresee future trends of real processes or phenomena; in effect there are different approaches: it is possible to concentrate on historical data (prediction based on the past), in modeling the reality (prediction based on the present) or even in reprocessing expert expectations (prediction based on the future); in general the most common used algorithms are based on mathematical algorithms re-elaborating historical data; this is mostly due to the fact that the creation of complex models requires much more efforts and customization, while the expert forecasts are usually not easy to be quantitatively elaborated adding further value; viceversa the time series analysis is easy to be adapted for a broad spectrum of applications.

Store organization represents a very important aspect to improve the overall performance of the Retail network; therefore to forecasts the workloads introduce the possibility to plan in advance the use of the resources and to guarantee that the service are always synchronized with the demand. However the requirements to support a planning system for a Retail store are much higher that that ones for an algorithm for predicting sales; in fact a store represent just a single node of a wide network and data statistical influence is not so high; in addition planning requires to consider multiple factors: i.e. activities for personnel are driven both by consumer demand (corresponding to cash barrier workload) and goods acceptance and preparations (corresponding to internal workload).

In addition it is important to mention that the data set are reduced even for the necessity to map each single store department (i.e. general goods, vegetables, cheese, meat, fish etc) and that the planning requirements is requiring to obtain a detailed behavioral evaluation of the workload along the days and the week. Based on this consideration the forecasts algorithms require to be very complex and to integrate different variables and factors to be fused together in order to achieve a better estimation of the system; however it is evident that an effective system in this area need to be able to self-tune and to be tailored for each specific department of each store, due to the specific characteristics of this behavior.

So the authors decided to use time series of different parameters and to combine them by data fusion algorithms, however in this case becomes critical to define the metrics for measuring the performance of the algorithms considering different aspects and to develop a methodology for optimizing the algorithm parameters in order to self optimize the system; this paper presents these aspect in relation to a case derived from the real application of this approach to a major Italian Retail Network (data have been modified due to the confidential nature of the original sets).

2. TIME SERIES COMPONENT IN RETAIL

Within the classical approaches in historical series analysis, the main components of a phenomena are supposed to results from the aggregation of different components:

- Trend: it represents the course of the historical series in the medium-long period respect the resolution of the data available; it changes in the time, but it doesn't present predictable cycles previously. Actually, don't exist simple specific techniques to analyze the trend, nevertheless if the trend is monotonous increasing or decreasing the analysis result to be very simple. Often an visual observation of the series allows to diagnose the presence of the trend. Sometimes it is necessary to eliminate the trend for further data elaboration, in this case specific methodologies are applied.
- Period components: these corresponds to oscillations around the mean values due to the expansions and the contractions of phenomena. These periodic components have multiple nature and correspond in Retail Store to:

1. Year Seasonal Components: represent growth or decrease of the activity due to specific events (Christmas, Easter etc.) or to specific periods: i.e. store in tourist areas during holiday timeframe are more active, while concurrently that ones in town are characterized by the opposite behavior. These sub-components depends on the location, climatic factor and social-cultural frameworks of the area, so each store have its own characteristics to be defined.
2. Month Periodic Components: during the month the demand have usually a periodic demand behavior due to the mostly concurrent distribution of salary to consumers (near the end of the month), so in Retail sales and related activities are affected by a fluctuation due to this aspect; usually this component have a limited influence on the store workload respect other ones.
3. Week Periodic Components: during the week the demand is very variable (i.e. friday and saturday) so this introduce a very strong periodic components.
4. Day Periodic Components: along the day the demand and activities are changing with peak timeframes.

- Error: it's the irregular component that introduce deviations. All historical series, that are not deterministic, have positive or negative irregularities, produced by stochastic factors. Usually it is acceptable the hypothesis (based on the fact that there are not systematic errors: i.e. data collections) that the Error is a random variable with zero mean, constant variance and not correlated.

In fact in retail historical series treated in this research refer to workload necessary to the different sales points of a major Italian retailer.

As anticipated the products of the great distribution are subject to yearly, monthly and weekly seasonal behavior and so related activities in retail store are affected by these components:

- the yearly seasonal behavior refers to the increase of demand for some kinds of product during particular periods of the year (Christmas, Easter, Summer…) and this corresponds often to an increase of workforce in the departments of these products;
- the monthly periodic component refers to economic factors, in particular to the consume of salaries. In fact, in the first 15 days of the month it's possible to observe a greater demand than the last days;
- the weekly seasonability reflects the habits of family: the first day of week is characterized by ordinary purchases to cover ordinary needs of week, while the purchases in the last days of week are extra purchases related to Sunday. Weekly workforce is characterized by peaks of work in the first day of the week both to respond to the demand both to allocate new promotional material and goods.

In addition during the store life-cycle many events occur that affect the behavior (i.e. competitor opening in the surroundings, strikes, power failure, etc.); the forecasts need to estimate the impact of these past punctual events for correcting the historical time series and to predict the presence in future of someone (i.e. day with extra opening time, special promotional week) for future events.

3. FORECAST MODEL

The historical data for forecasting the retail store workload have been defined based on a structure that characterize each point of sale and each department.

The basic element is the department, each department belongs to a store and each store belongs to a retail cluster.

Each department is characterized the following data:

- TimeFramed Data (TFD): data related to the evolution of the independent variable along the day collected each quarter of an hour (customers, sales, working hours);
- Date and Flow Data (DFD): data related to the evolution of the independent variable along the

weeks/months/years summarized day by day (customers, sales, working hours, arriving pallets);

- Calendar: include the details of the operating hours and the definition of events (past or futures) and their estimated/expected impact on the different independent variables.
- Department Characterization: all the calibration parameters of the algorithms for the specific sector. Since previsions are subject to different stochastic factors, it is necessary to correct them with calibration parameters that reduce the deviation between real data and prevision data.

The forecast model, developed by authors, combines the different data of the 96 quarters of an hour of the day (timeframed) and of the days (data&flow); the results of these two data set some time don't corresponds due to administrative changes and corrections, in addition their comparison allows to complete consistency tests. The data set are expected to be provided by company ERP (Enterprise Resource Planning) and the personnel presence system in multiple session to allow the update of data to be corrected by managers and administrative procedures; in fact in order to improve accuracy on the forecast input data are corrected by specific parameters (i.e. event impact on past data). The model processes input files based on the data structure above described in term of TimeFramed Data, Date and Flow, Calendar and Departments.

Forecasts are generated for each store and structured based on two main data set: FOT (Forecast Organized by Timeline) and FOD (Forecast Organized by Date) corresponding respectively to the evolution along the day and over weeks; they include the target functions related to customers, sales and pallets and working time; in fact the final goal for planning and store organization is to forecast working hours so the other target functions have to be considered as supporting information.

In the case study the authors developed a tailored model for the users integrated with the company ERP able to generate and distribute the forecasts for next weeks; historical and prevision data are available for two years along the day and for five months in term of daily evolution.

In the case study proposed the network is composed by twelve stores each one including five departments:

- department 1: general goods;
- department 2: deli and dairy products;
- department 3: fruits and vegetables;
- department 4: butchery;
- department 5: fishmonger.

FOD and FOT are save in files for each stores of each point of sail of the retail network and distributed to the stores; a specific tool for post-processing the forecasts in order to include store manager preferences and final tuning was developed by the authors and installed in the stores.

4. THE CALIBRATION PROCEDURE

To identify optimal parameters for algorithms tuning the authors defined a specific metrics based on error indicators able to measure deviation between forecast and real data. In fact forecast algorithms are strongly depending on calibration parameters related to the department that need to be optimized based on specific behavior profile; this need to be identify based on historical data analysis. To identify the optimal parameter sets, in term of deviation reduction between real data and forecasts, the authors developed a calibration procedure based on four different error indicators; these are devoted to measure the forecast errors and to evaluate the algorithm parameter set efficiencies. The metrics developed consider both the conceptual forecast error and the use of forecast itself; based on these consideration the authors identified the following indicators:

- J_1^j is an index, for j-th target function, derived by MAD (Mean Absolute Deviation), for the calculation of the absolute error of daily workload.

$$J^j{}_1 = \sum_{k=1}^{7\cdot m} \frac{\left| DFDr^j{}_k - DFDf^j{}_k \right|}{7\cdot m} \tag{1}$$

- m: number of weeks under evaluation;
- $DFDr^j_k$: real Value of j-th DFD target function on the day k-th;
- $DFDf^j_k$: forecast Value of j-th DFD target function on the day k-th;
- J_2^j is an index, for j-th target function, that absolute measures the error of daily workload.

$$J^j{}_2 = \sum_{k=1}^{7\cdot m} \frac{DFDr^j{}_k - DFDf^j{}_k}{7\cdot m} \tag{2}$$

- J_3^j is an index, for j-th target function, derived by MAD (Mean Absolute Deviation), for the calculation of the absolute error of the daily workload in each quarter of an hour.

$$J^j{}_3 = \sum_{i=1}^{672\cdot m} \frac{\left| TFDr_i^j - TFDf_i^j \right|}{672\cdot m} \tag{3}$$

- $TFDr^i_k$: real Value of i-th TFD target function on the day k-th;
- $TFDf^i_k$: forecast Value of i-th TFD target function on the day k-th;

- J_4^j is a comprehensive weighted target function that represent an index able to represent the sum of the other indicators.

$$J_4 = k_1 J_1 + k_2 \left| J_2 \right| + k_3 J_3 \qquad (4)$$

- k_1, k_2, k_3,k_4: factors for balancing the weighted average of the performance indexes.

The calibration parameters are tuned in order to optimize the J_1, J_2, J_3 and J_4. In particular the authors decided to fix a set of correcting factors (k_1 k_2 k_3 k_4) and to proceed in the optimization of the parameters mostly by minimizing J_4.
The calibration procedure, to be repeated for each single department of all the stores, is following:

- Preprocessing analysis on input data set:
1. Calendar, TFD, DFD Format Check;
2. Calendar Consistency Check;
3. Comparison DFD vs. Store Template Profile;
4. Comparison TFD vs. Store Template Profile;
5. Comparison DFD vs. TFD and difference motivation.

- General Optimization:
1. Automated Optimization for each error index over a wide range of analysis;
2. Comparison of the J_1, J_2, J_3 and J_4 error indexes and tuning of k_1, k_2, k_3 and $k_4$factors.

- Fine Tuning:
1. Automated Optimization in small range of analysis for J_4;

- Update of Algorithm Parameters;
- Test of the performance achieved on data not used for forecasts (i.e. one or two more weeks).

Based on above described procedure, it is possible to define the best parameters for each sales point of a distribution network.

In fact it is pretty important to divide the historical data in order to keep available for testing last weeks; in order to achieve this results it is suggested, during the test phase, to complete the analysis on the time series with the exception of the last two weeks; these data will be used during the test phase for validating the robustness of the configuration.

As example of calibration it is proposed the case of general good department of one store of the network in the case study proposed.
In the case the general optimization results of the analysis are presented in relation to the change in one of the department parameters.

Table 1: Different Errors Comparison

Param.	J1	J2	J3	J4
10	25.05%	24.53%	37.81%	3819.95
20	20.67%	17.74%	33.06%	3316.10
30	17.45%	10.98%	28.92%	2888.20
40	18.38%	4.04%	26.57%	2699.95
50	21.39%	-2.68%	25.99%	2708.40
60	26.73%	-9.61%	26.87%	2892.40
70	31.04%	-15.43%	29.01%	3165.90
80	37.47%	-23.43%	33.03%	3646.55
90	41.99%	-28.39%	36.06%	4002.05
100	50.39%	-37.30%	41.89%	4681.80

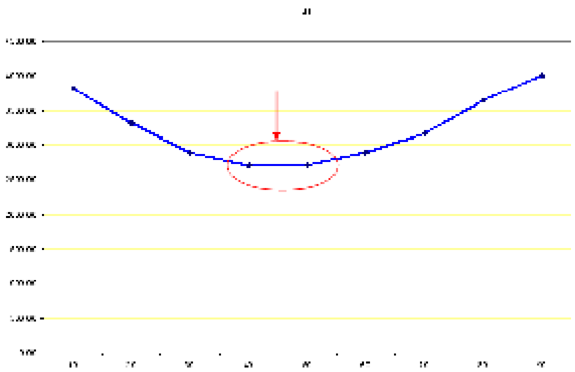

Figure 1: Identification of Fine tuning Area for J_4

From graphs and tables it's possible to observe that the J_4 best values are concentrated in range 35 - 55 of the parameter under optimization; completing a detailed analysis in the surroundings the results are the following:

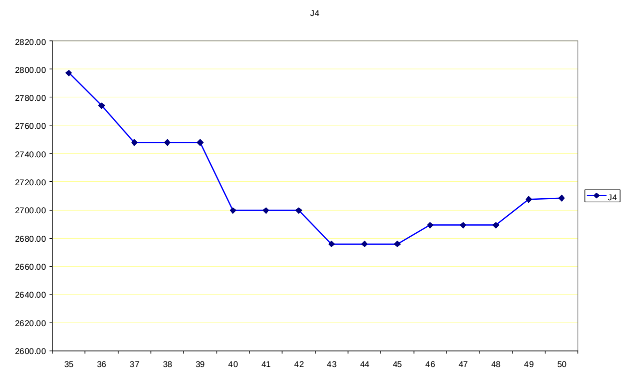

Figure 2: Fine Tuning of J4 in the proposed case

Table 2: Error Indexes during Fine Tuning

Param.	J1	J2	J3	J4
35	17.35%	8.15%	27.91%	2797.25
36	17.54%	6.87%	27.60%	2774.00
37	17.74%	6.02%	27.26%	2747.90
38	17.74%	6.02%	27.26%	2747.90
39	17.74%	6.02%	27.26%	2747.90
40	18.38%	4.04%	26.57%	2699.65
41	18.38%	4.04%	26.57%	2699.65
42	18.38%	4.04%	26.57%	2699.65
43	18.84%	1.94%	26.19%	2675.90
44	18.84%	1.94%	26.19%	2675.90
45	18.84%	1.94%	26.19%	2675.90
46	19.66%	0.21%	26.16%	2689.15
47	19.66%	0.21%	26.16%	2689.15
48	19.66%	0.21%	26.16%	2689.15
49	21.09%	-2.11%	26.04%	2689.15
50	21.39%	-2.68%	25.99%	2707.45
51	21.39%	-2.68%	25.99%	2708.40
52	21.39%	-2.68%	25.99%	2708.40
53	21.39%	-2.68%	25.99%	2708.40
54	23.85%	-5.94%	26.27%	2708.40
55	24.40%	-6.72%	26.36%	2782.15

In the same way all calibration parameters are defined for each target function of each departments of the network.

5. COMPARING PERFORMANCES

The analysis for optimizing the forecast algorithms is pretty articulated; it was identified the necessity to forecast the workload for each quarter of an over over next weeks for each department of each store of the network.

In order to proceed in this sense and provide possibility to have daily up-to-date analysis it was necessary to combine data related both to detailed evolution (immediately available and pretty time consuming for processing) and to day summary (including corrections and easy to process but available later).

In addition the forecast performance changes over the time due to the fact that the system needs periodic tuning; considering the stochastic component it is pretty difficult to maintain a clear understanding of the problems that is articulated over different directions that are synthesized in the following:

- Store/Department Explosion of variables;
- Periodic check for monitoring forecasts performances along the time;
- Day vs. Week prediction for allocating resources.

In addition different target functions have been defined and even if for the case proposed the working hours are the main factor it is evident that the check about goods arrivals (pallets), sales and customers are pretty interesting for planning activities and need to be keep under control for providing a reliable support to store managers.

Due to these reason the authors developed a solution for complete analysis over the different direction of investigation on the forecasting results; this solution was defined as Drawer and it provides the possibility to automate the optimization process by defining the scenario to be investigated in term of timeframe, target function, store, department etc. The Drawer allows to fix the range of analysis and the investigation resolution as well as the optimization algorithms and all its parameters. The system perform in sequence all the different set of steps required by the proposed methodology and provides results in term of tables and graphs for each one in order to allow the analyst to complete a review. In addition the drawer export the files for automated configuration of the forecast algorithm in order to guarantee an easy and periodic update of the forecast algorithm optimization.

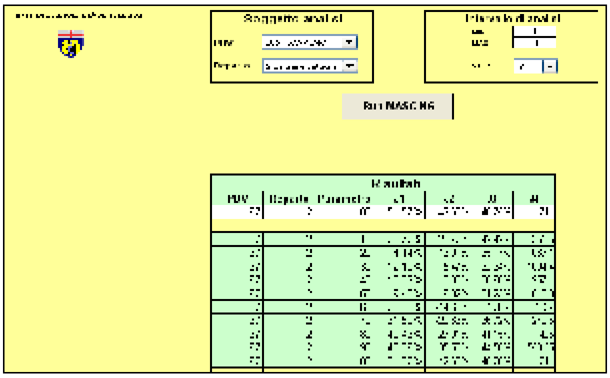

Figure 3: Interface of Drawer

The drawer process directly the source database DFD and TFD available for the forecasting algorithms and analyze the results generated in FOD and FOT databases. The comparison are based on: out_t, out_d analysis; out_t contains comparison of real and forecasts for TFD data, while the out_d focuses on DFD data; it is interesting to note that the analysis of the performance on DFD, corresponding to check the total working hours required for each day of next week need compared the FOT integrated over the day in order to check consistency of detailed planning hour by hour.

Moreover the data in out_t and out_d are used to check the performance indexes evolution.

For instance, in the case in analysis, are proposed two different results as following:

- TFD vs FOT. It’s a line diagram, that represents the workload profile required in each quarter of an hour along the days of future weeks based on forecasting algorithms respect real data; this is presented in the following.

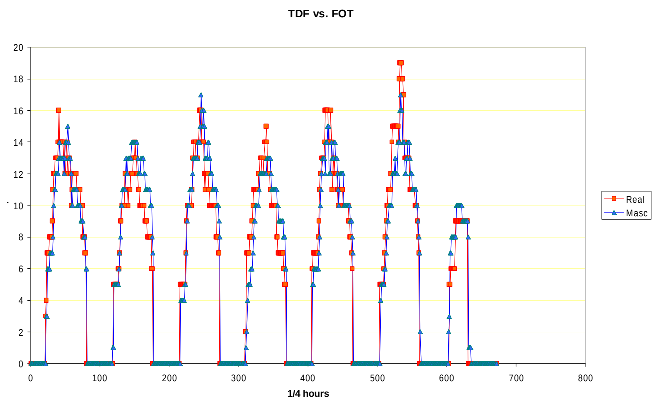

Figure 4: TFD vs FOT

- DFD vs integrated FOT. This bar diagram, that proposes the comparison between daily workload (h/day) during the period of analysis respect the forecasts provided by the algorithm in term of FOT.

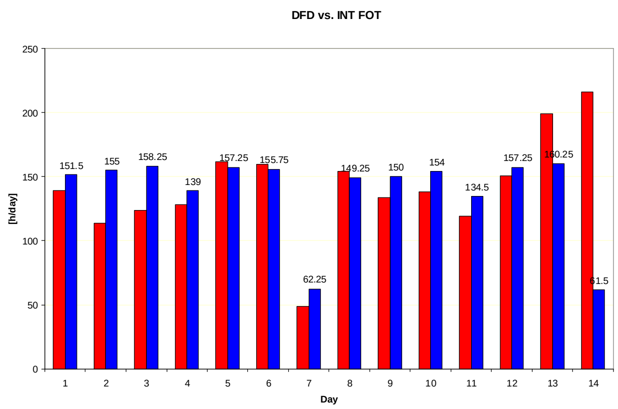

Figure 5: DFD vs integrated FOT

6. CONCLUSIONS

The methodology proposed was applied over a small cluster of stores on a wide retail network as pilot; the results was very promising in term of efficiency of the algorithms and reliability of the methodology.

In fact the proposed example allowed to validate a quick and robust methodology for forecast algorithm tuning that create a periodic updating calibration procedures.

Therefore the forecast model after the parameter optimization improved its performances of about 60%, reducing the deviation between real data and forecasts for all sales points and obtaining results that are very satisfactory based on store expert point of view. Moreover the use of Drawer allows to automate the calibration procedure reducing the efforts required in term of skills and time and guaranteeing the introduction on the company of a systematic procedure

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