Advanced M&S for Innovative Technologies Applied in Retail Sector

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Goals of the Research

This paper propose the use frequency domain modeling (FDM) methods for optimizing the inventory management in retail supply chain

FDM is strategic in order to identify periodic component influence and to support demand forecasts within a very stochastic framework.b

Algorithms

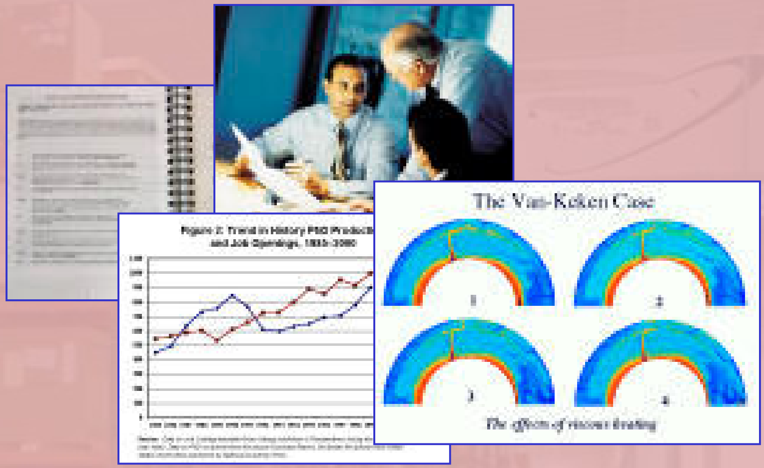
Among other algorithms the following wasanalyzed as standard solution available to SAP R/3 Users:

- **Mobile mean**
- **1st Degree Exponential Smoothing**
- **2nd Degree Exponential Smoothing**
- **3rd Degree Exponential Smoothing**

Simulation & Forecasts

Forecasting techniques are devoted to extract in the most efficient way Knowledge from various Input for improving Forecasting Capabilities

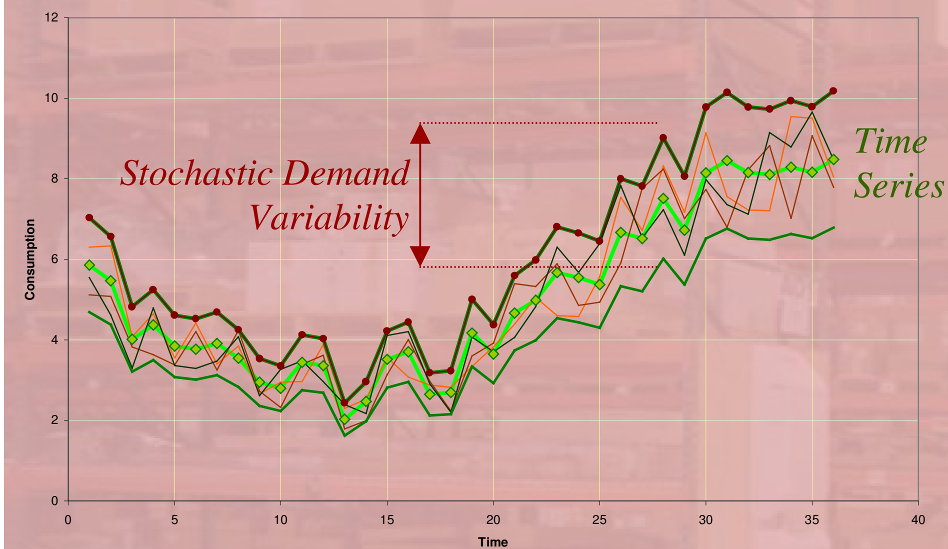
Historical Data
Expert Estimation
Phenomena Symptoms
Boundary Conditions



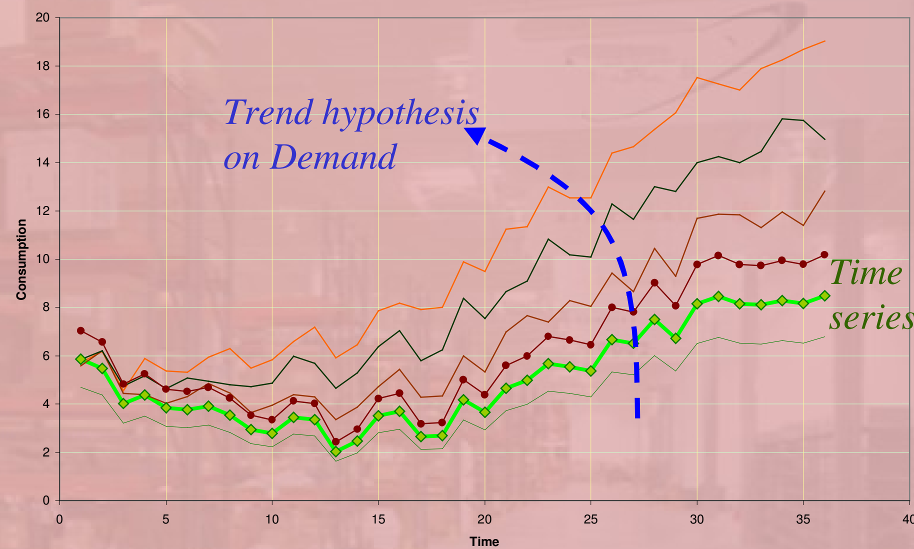
Modeling & Simulation can be used for testing Forecasting Techniques and for Measuring their Performances over complex scenarios

Stochastic Simulation

The Stochastic Simulation allow to verify the robustness of the different algorithm, we have to consider the following component combination on the time series to obtain the test scenario.



Stochastic Punctual Variations



Trend Components

The Simulator carries out the tests on different replications and it makes an average of the obtained results on the different scenarios.

Advanced Forecasting vs M&S

- ✓ **Advanced techniques can improve the Capability to Predict a Real System respect traditional methods**

- ✓ **Modeling & Simulation is still necessary to measure robustness and efficiency of the Forecasting System**

Forecasting in Logistics

In logistics and supply chain management Forecasting is used in order to:

-Estimate the Customer Demand

-Estimates Market Evolution

-Support Inventory Management

-Support Production Planning

Algorithm Comparison

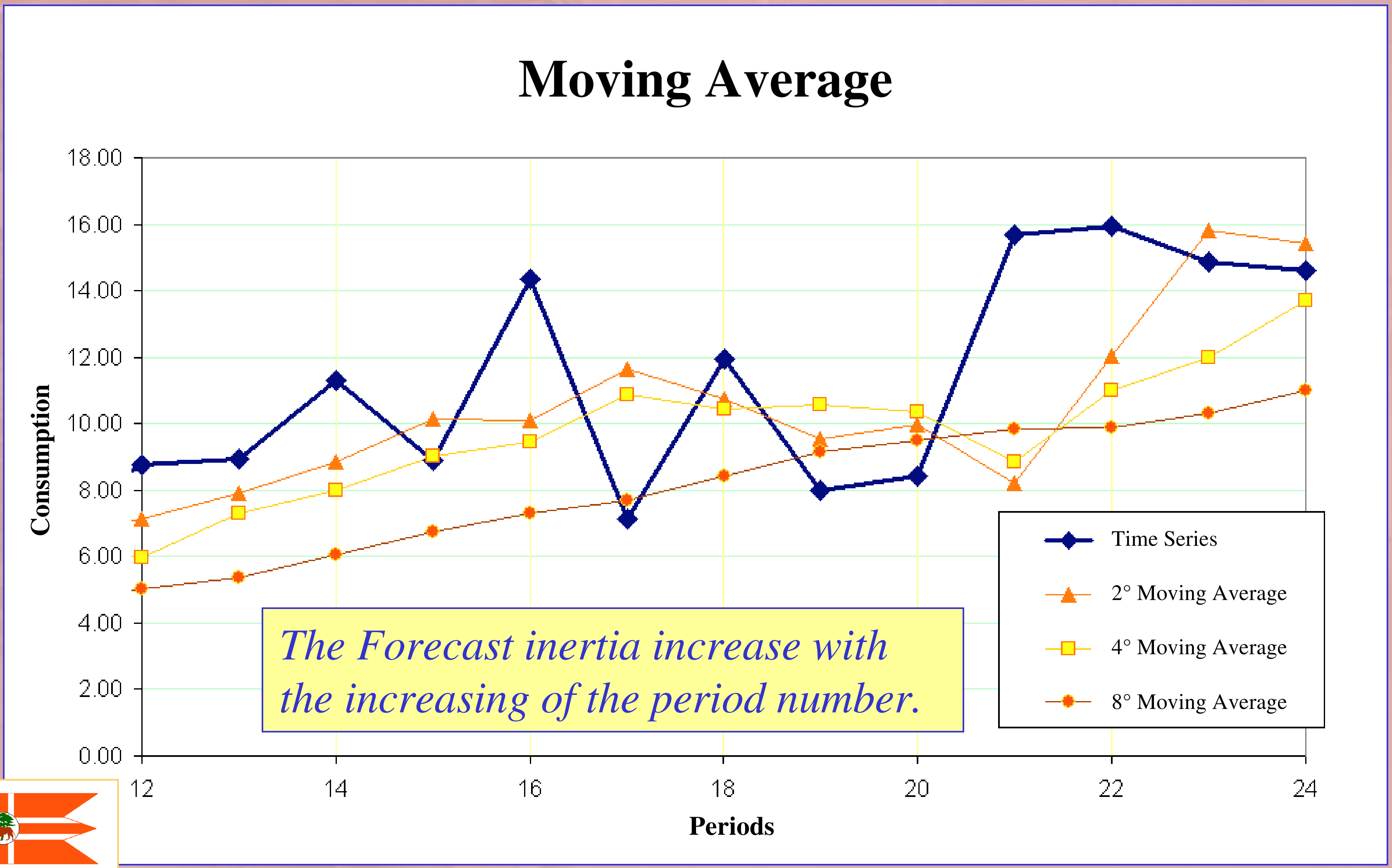
COST/BENEFITS	Influence of Most Recent Data	Less Data Required	Identification of new Trends	Season and Period Identification	Risk to Over Estimate Trend	Risk due to Forecasting Inertia	Critical Influence of Peaks	Complexity of the Model
Moving Average	no	no	no	no	no	yes	no	
Weighted MA	yes	no	no	no	no	yes	yes/no	
Single Exp.Smoothing	yes	yes	no	no	no	yes	yes/no	Growing
Double Exp.Smoothing	yes	yes	yes	no	yes	yes/no	yes	
Triple Exp. Smoothing	yes	yes	yes	yes	yes	yes/no	yes	

Each model has specific features; we have to pay attention about the Robustness, that is the capability to suggest optimum results even if there are aleatory components to disturb the scenario.

It is necessary to guarantee a management and accurate settings of the forecast algorithms parameters in order to represent the reality evolution.

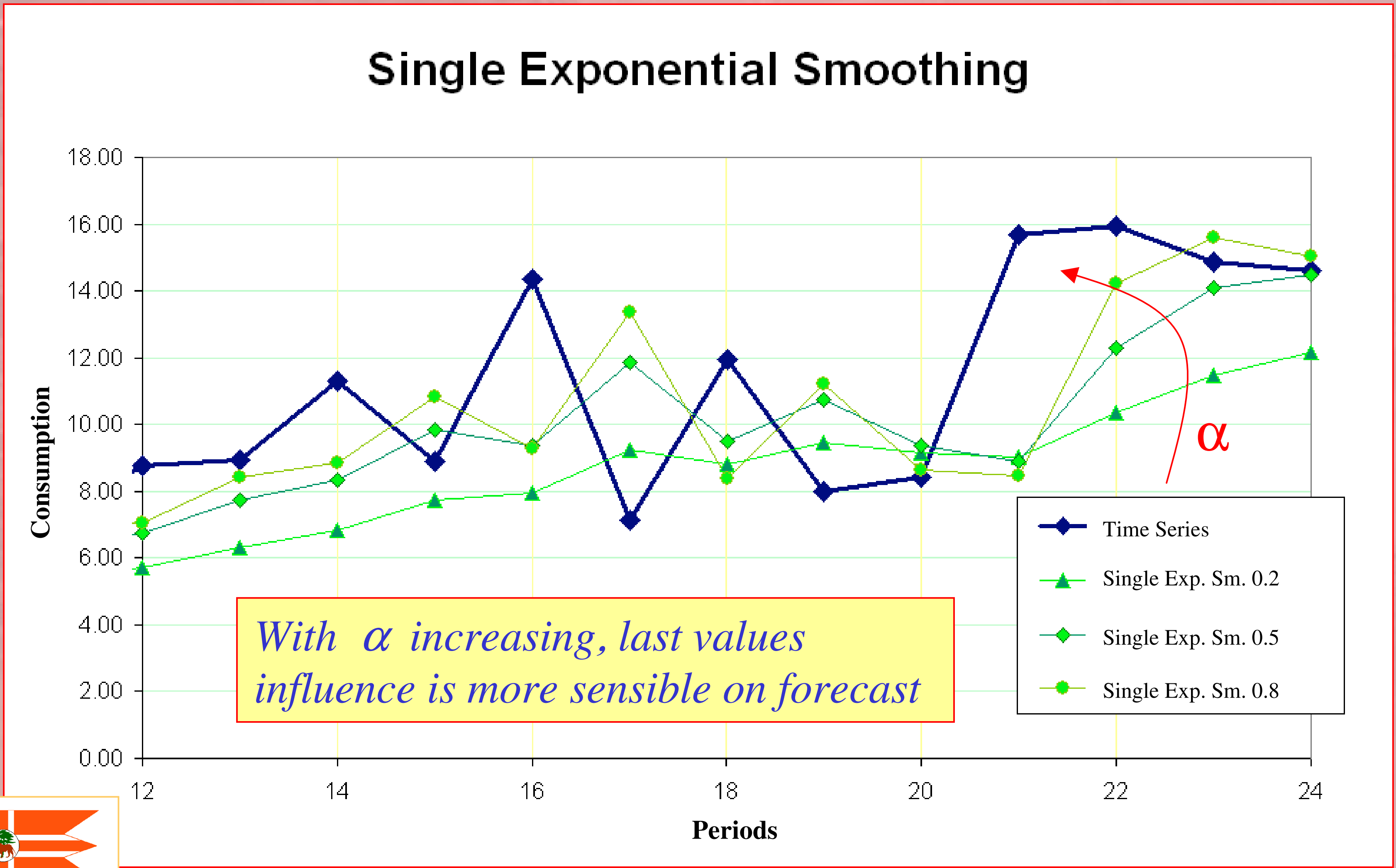
Forecast vs. Time Series

Moving Average Examples



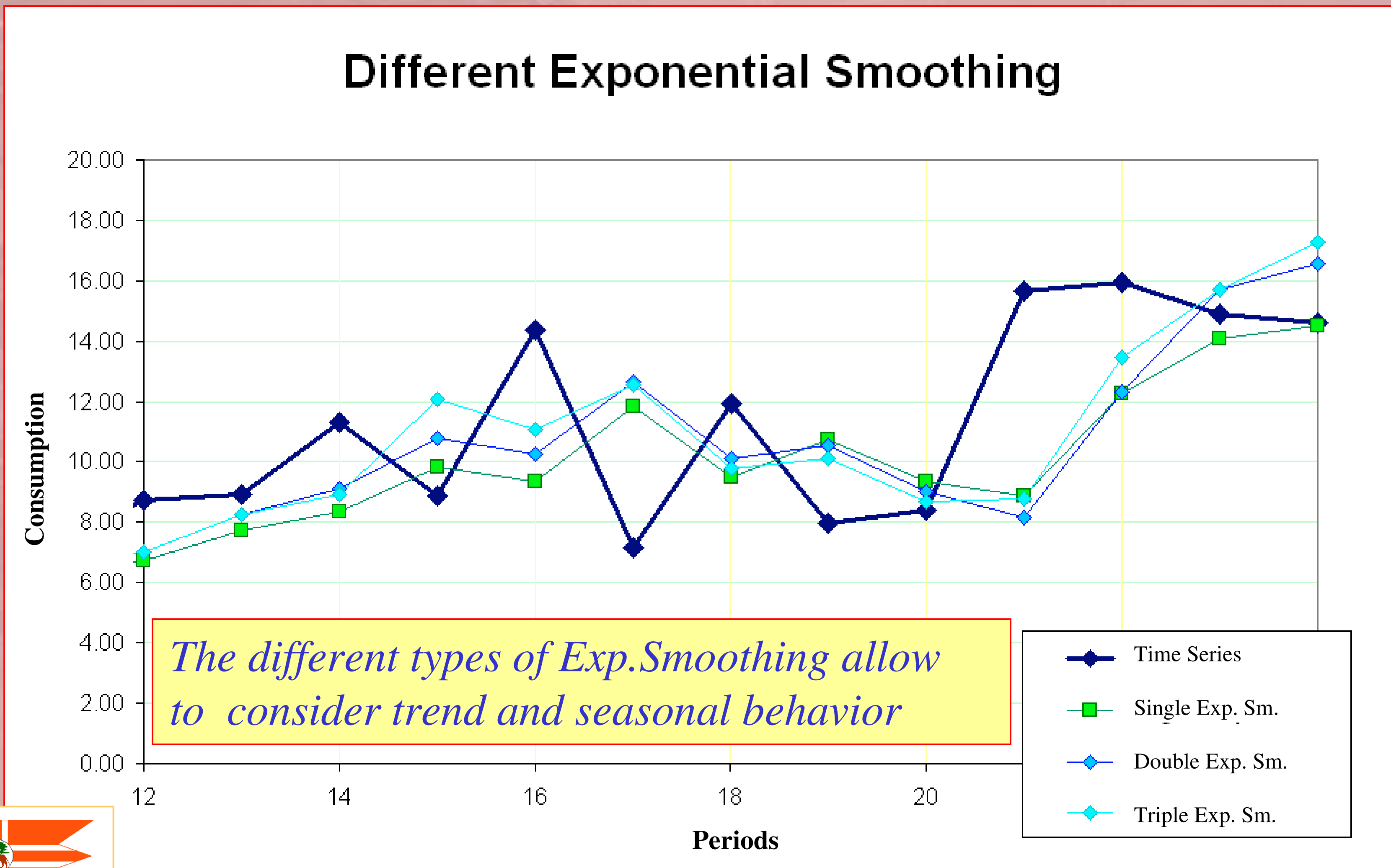
Forecast vs. Time Series

Exp. Smoothing Examples



Forecast vs. Time Series

Single vs. Double vs. Triple



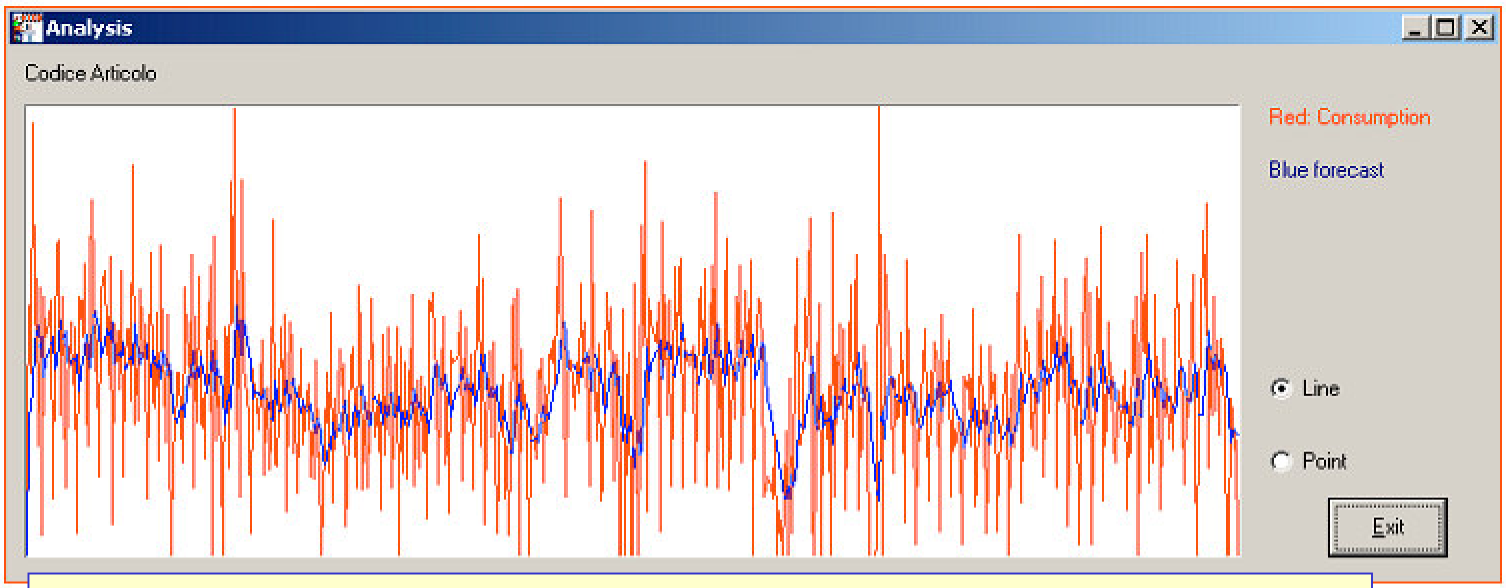
Seasonal Period Analyses

A prior knowledge of a probable seasonal period in the time series allow to know better the studying scenario and to carry out strategic forecast on the real case study at the same time.

For some Forecast algorithms (i.e. Triple Exponential Smoothing) the seasonal period of time series is an input data.

We has estimate the seasonal period converting the time series in the frequency range.

Example from a Realistic Case



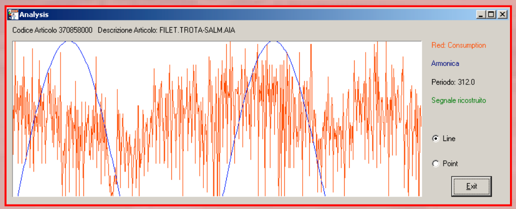
Typically real behaviors with strong stochastic component and high values of Standard Deviation respect the mean value

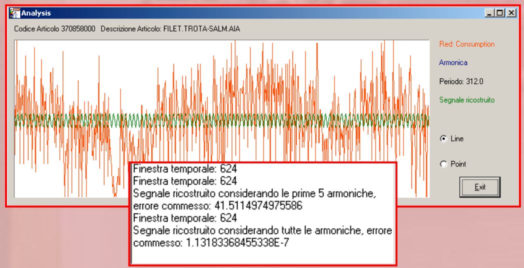
Period Analysis

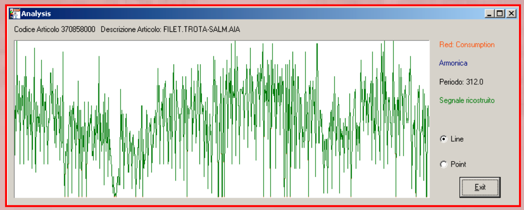
In order to identify a priori possible seasonal behaviors on the demand it is useful to acquire knowledge related to the processes under analysis and to its characteristics.

Some predictive algorithms (i.e. Triple Exponential Smoothing) have parameters considering the periodic component in time series.

By a frequency analysis based on Fourier transform it is possible to identify the impact of periodic components.

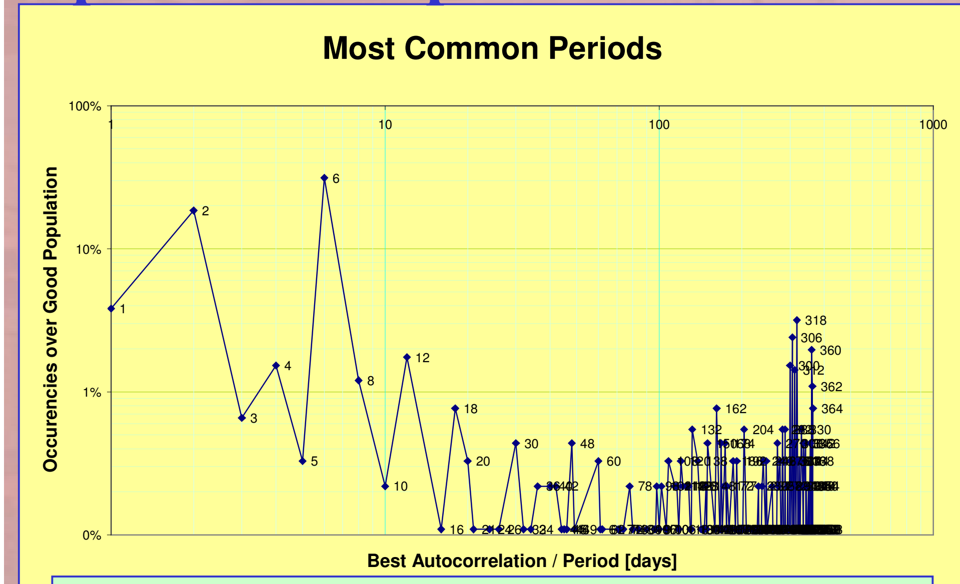


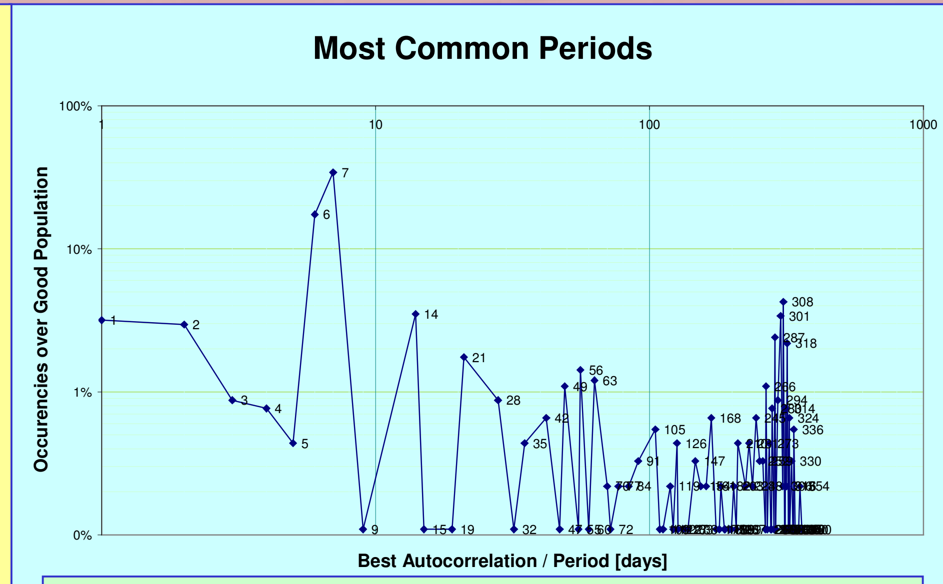




Autocorrelation Analysis

Autocorrelation analysis allows to identify the most significant periodic component over a time series.

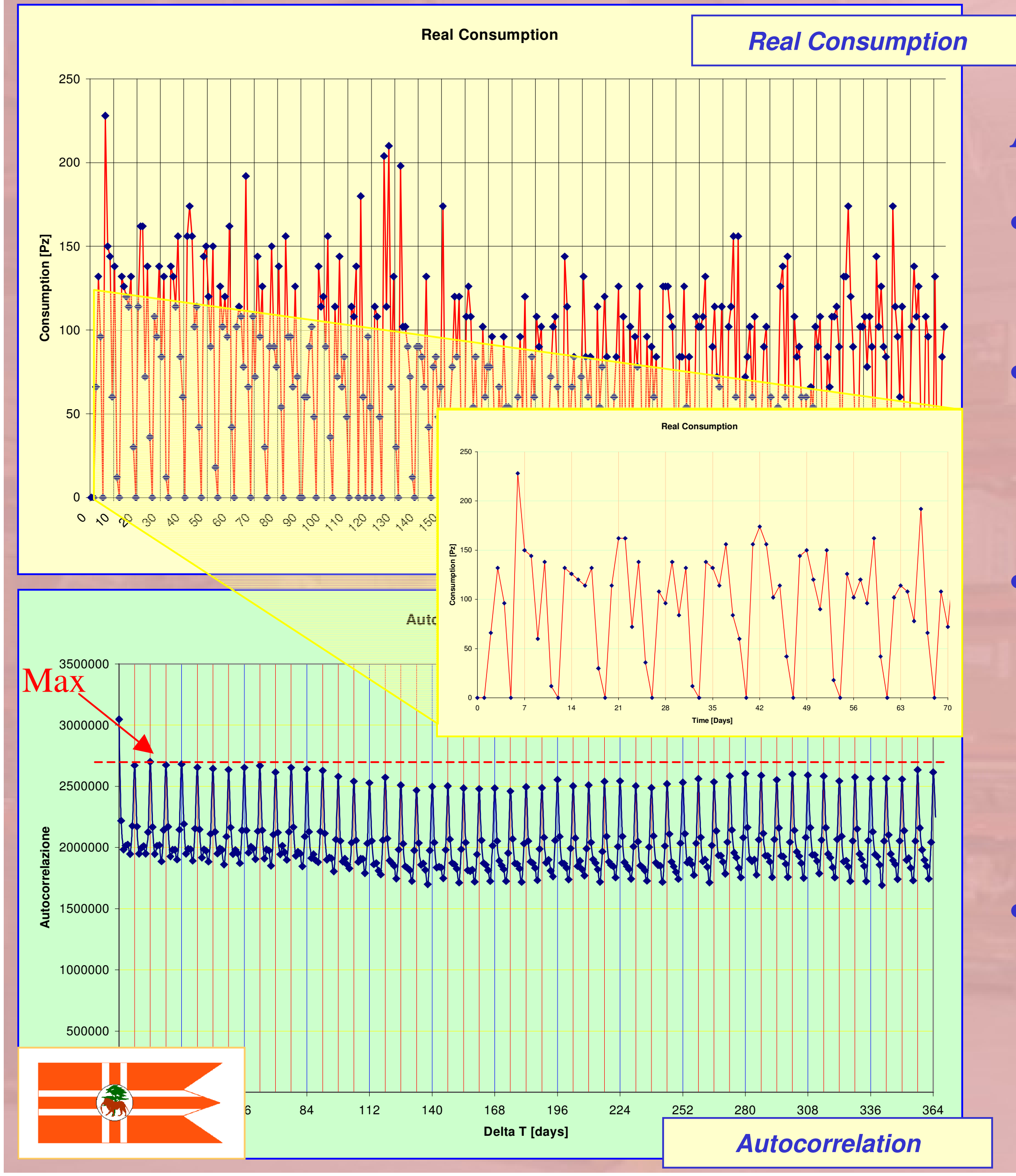




These figures are related to the case study proposed about the demand of frozen goods. These figures consider the week without Sundays (due to the delivery policies in use) it is evident that six days and multiple periods are the most common and significant periodic component.

In this figure the same representation is proposed considering weeks including all the days; in this case the most significant period is seven days and its multiples so is evident that consumption of these goods are characterized by week periodic behavior.

Autocorrelation Example



Autocorrelation Analysis

- Autocorrelation highlights the presence of periodic components
- In this case the behavior seems including high random components (noise)
- Autocorrelation have is max value in correspondence with 7 days. However this value is just a little bit higher than other time shifts
- Zoom on a time windows it is evident that the week periodic component is present but not too much significant

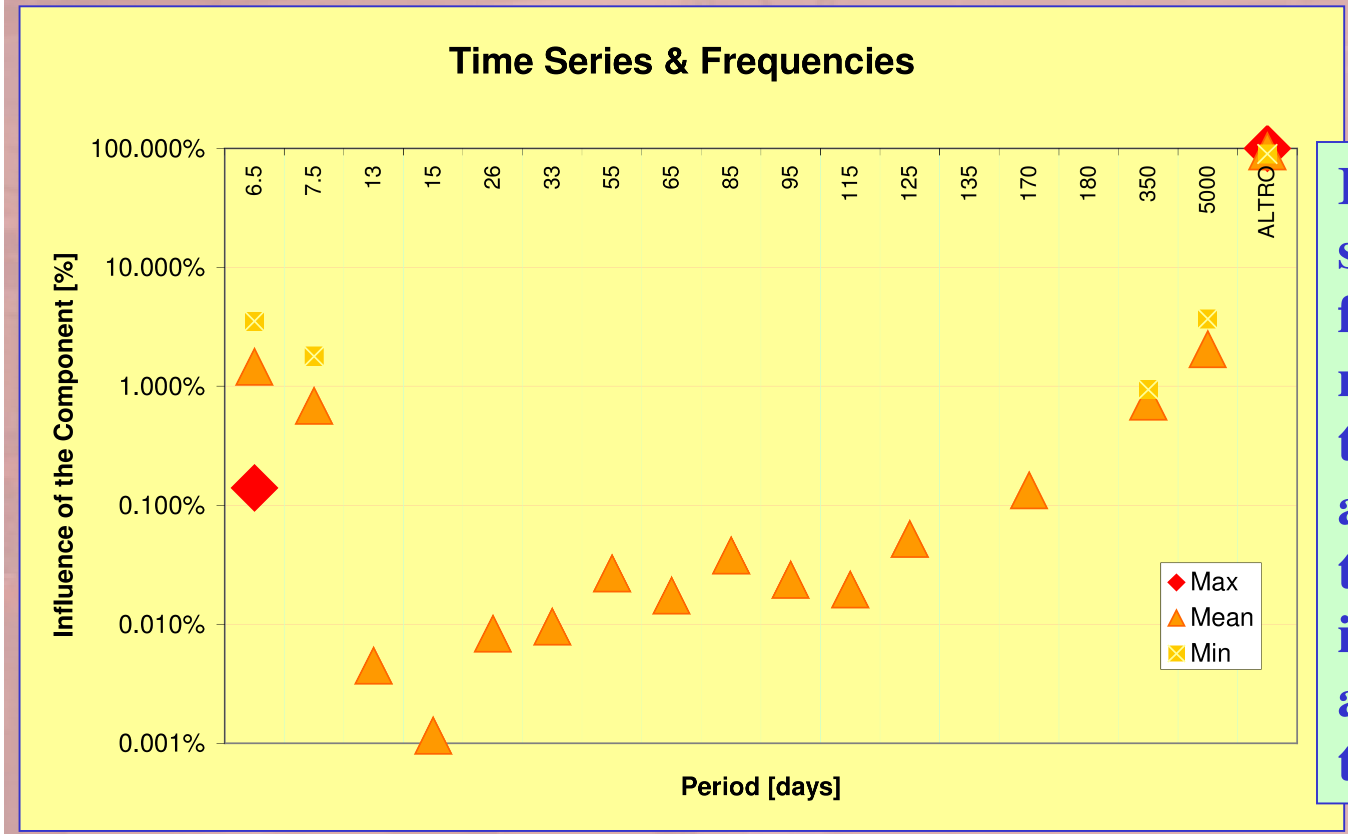
Stochastic and Periodic Components

By Fourier Analysis it is possible to:

- Define the periodic component influence over the time series.
- Main Frequency in this case reproduces just qualitatively the overall behavior.
- It is evident that in the proposed case the combination of first five frequencies have very low reproduction capability over this historical behavior.
- The overall periodic behavior can be reconstructed just by adding all the high frequency components (noise).

Different Periodic Components Analysis

Using the Fourier Series Methodology we identify the frequency's influence determined on the each time series behavior.



In our case, even if the six and seven days frequencies are the most significance together the semester and the annual one, their influence is less important then aleatory components in the time series (ALTRO).

The M.A.D. Calculation

We have choose the M.A.D. as optimization parameter because in a complex scenario it allows to obtain number easier to manage.

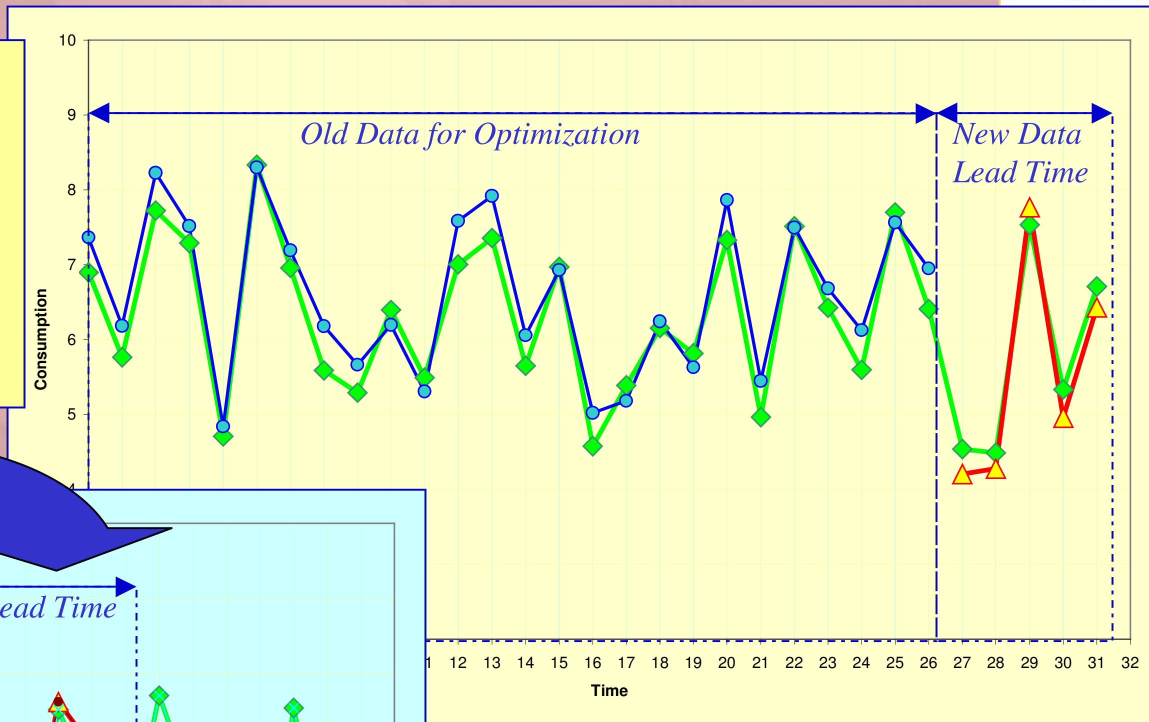
In the case study proposed the M.A.D.calculation was made in two different ways:

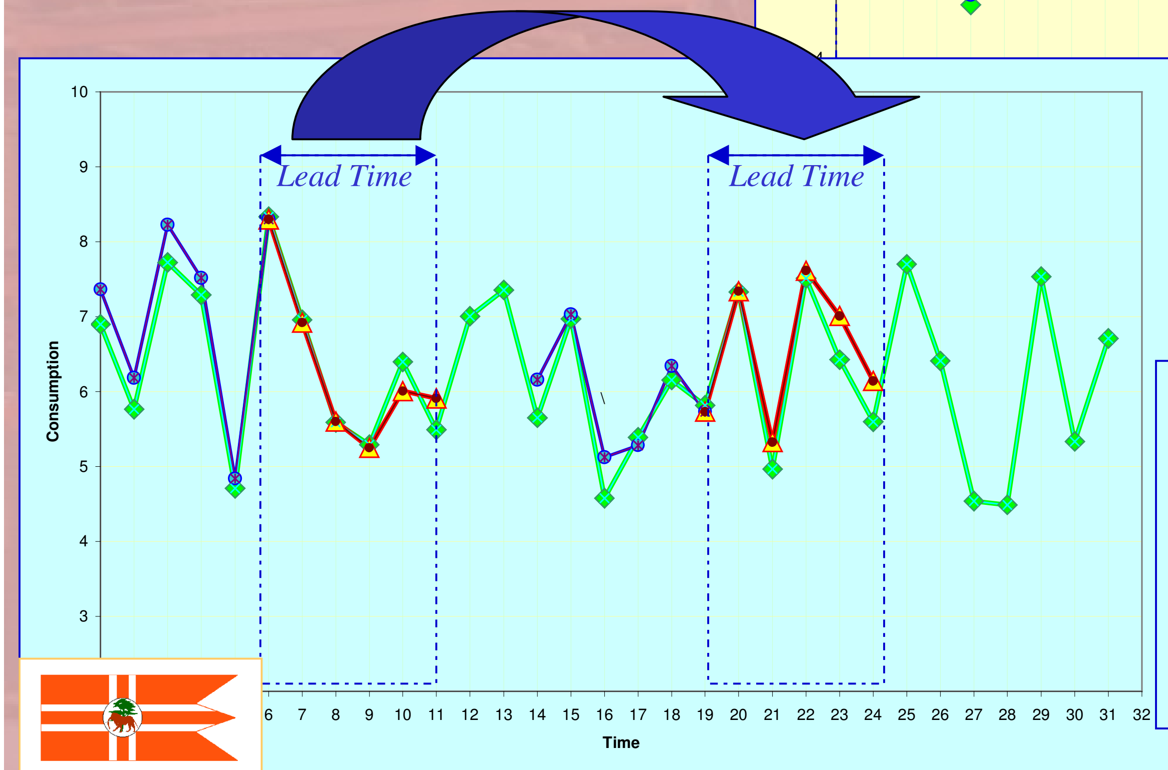
- Lead Time M.A.D.: the forecast is carried out on the Lead Time and the delta among forecast and the time series are calculated.
- Future M.A.D.: the time orison is divided in two part, the first part is the total scenario less then the lead time and the other one is the lead time. On the first part the algorithm is optimized and on the second part the selected optimum one is tested.

The Future M.A.D. emphasize in a clear way the real performance of the selected algorithm.

The different M.A.D.

- **Mean MAD in Last Lead Time**
- **Parameters Optimized on MAD over “Old” Data**
- **Tested and Measured over “New” Data**





- **Mean MAD in Lead Time over Complete Time Series**
- **Parameters Optimized on MAD over All Data**
- **Tested and Measured over All Data**

A Case Study for Understanding

We will analyze a case study as example of synergy between simulation and forecast techniques.

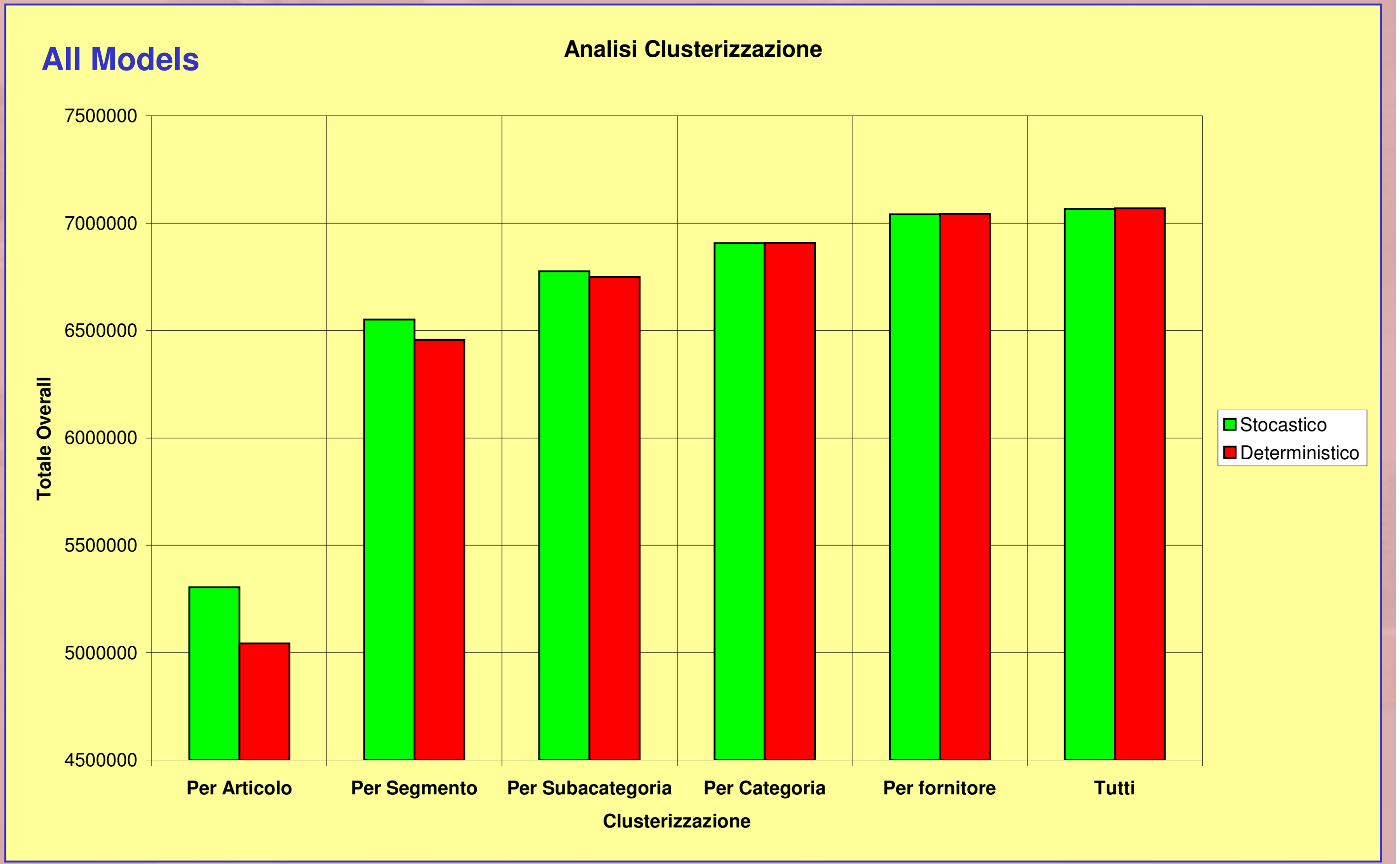
The case is related to frozen goods over a regional area with about 30 millions inhabitants involving about 1470 types of item from 90 suppliers organized in categories 96 with 33 subcategories and 11 product segments.

Demand is based on historical data about quantities delivered daily over the supply chain.

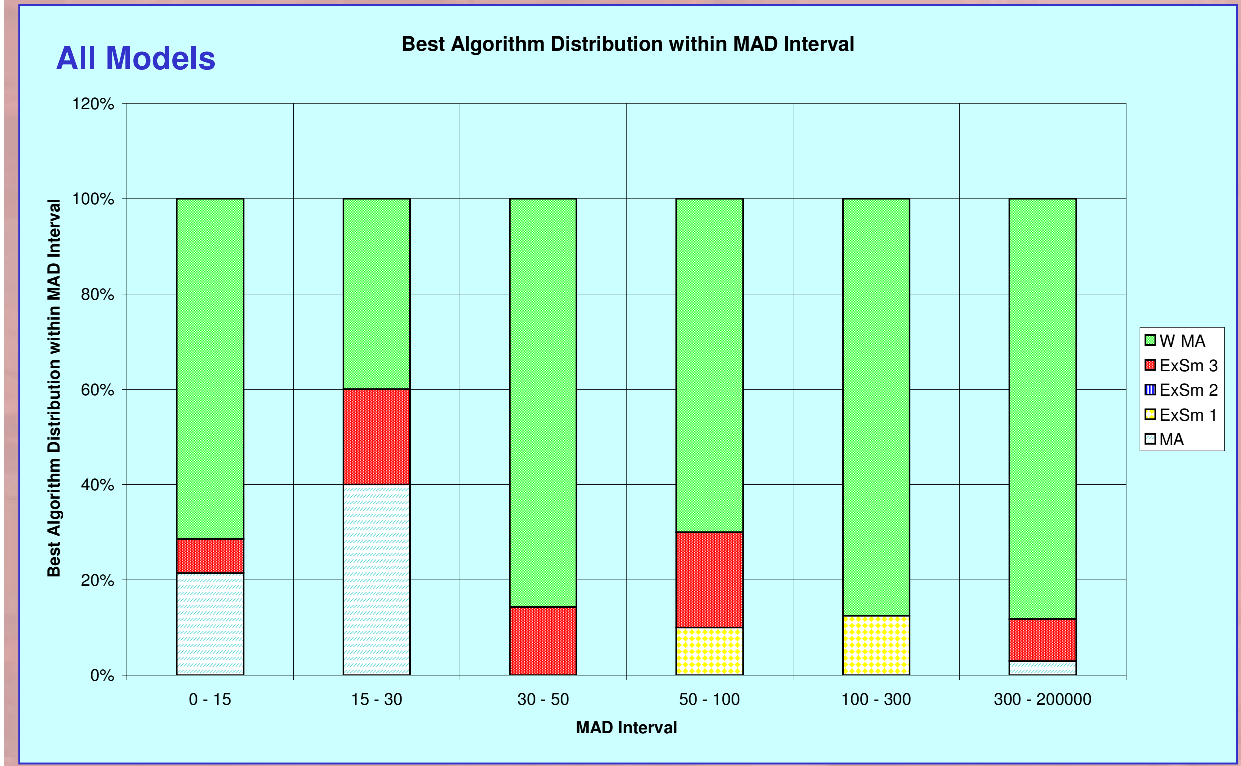
Clustering Analysis

Due to the different possible ways to group items we carried out an analysis to determinate the minimum number of errors in order to define the best algorithm and the parameters fitting for clusters.

The analysis identifies that the Product Segment is the best cluster (not considering the single Item).



Product Segments Cluster Lead Time M.A.D.

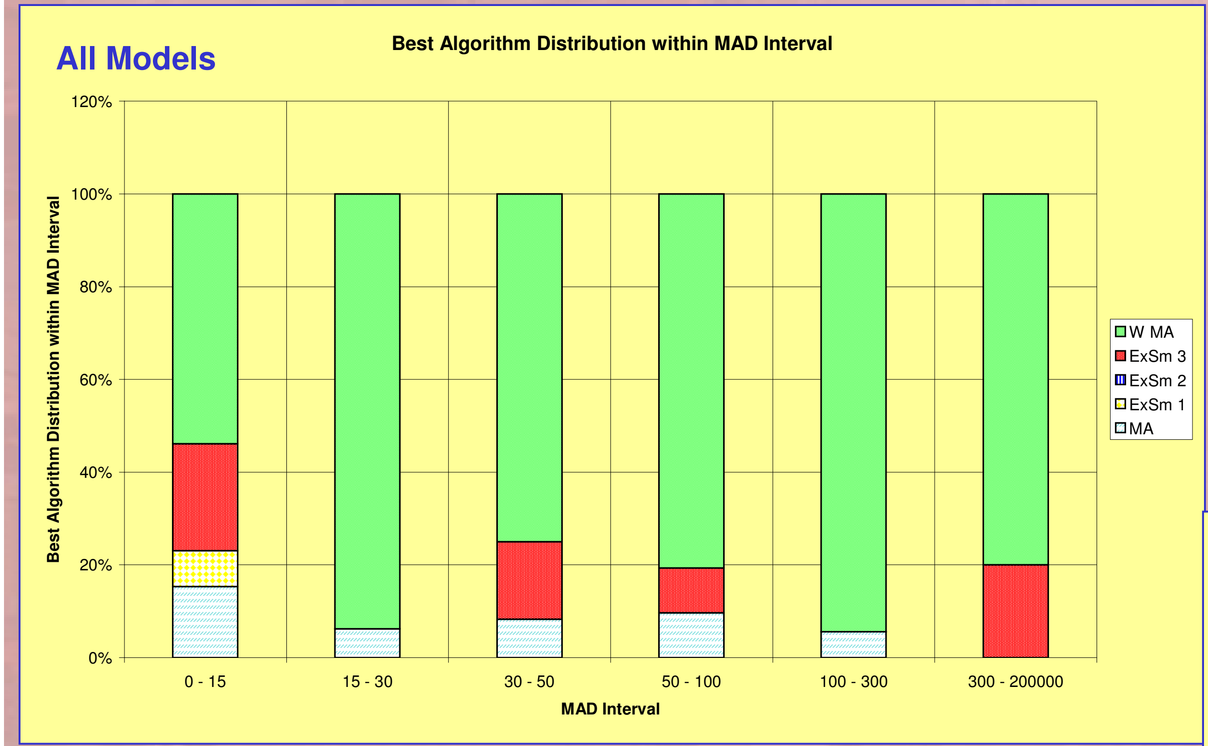


Single and Triple Exp. Smoothing have a small effect in the scenario.

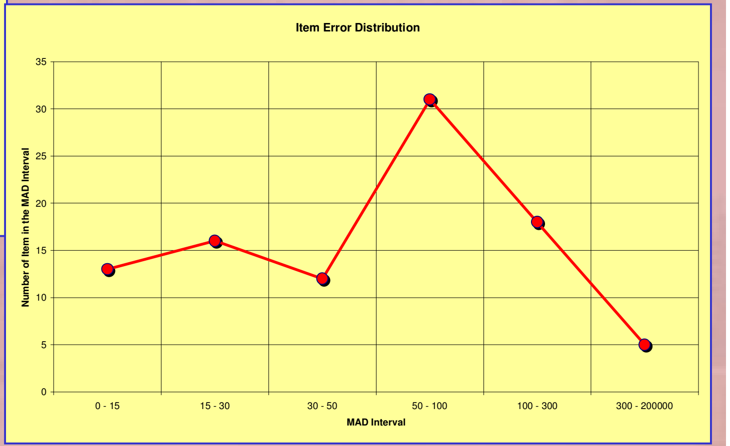
The Double Exp. Smoothing has not influence at all.

If we divide the M.A.D. in intervals, we can see that the most important algorithm is the Weighted Moving Average for high and low error values, while the Moving Average has influence only in the low values.

Product Segments Cluster Future M.A.D.

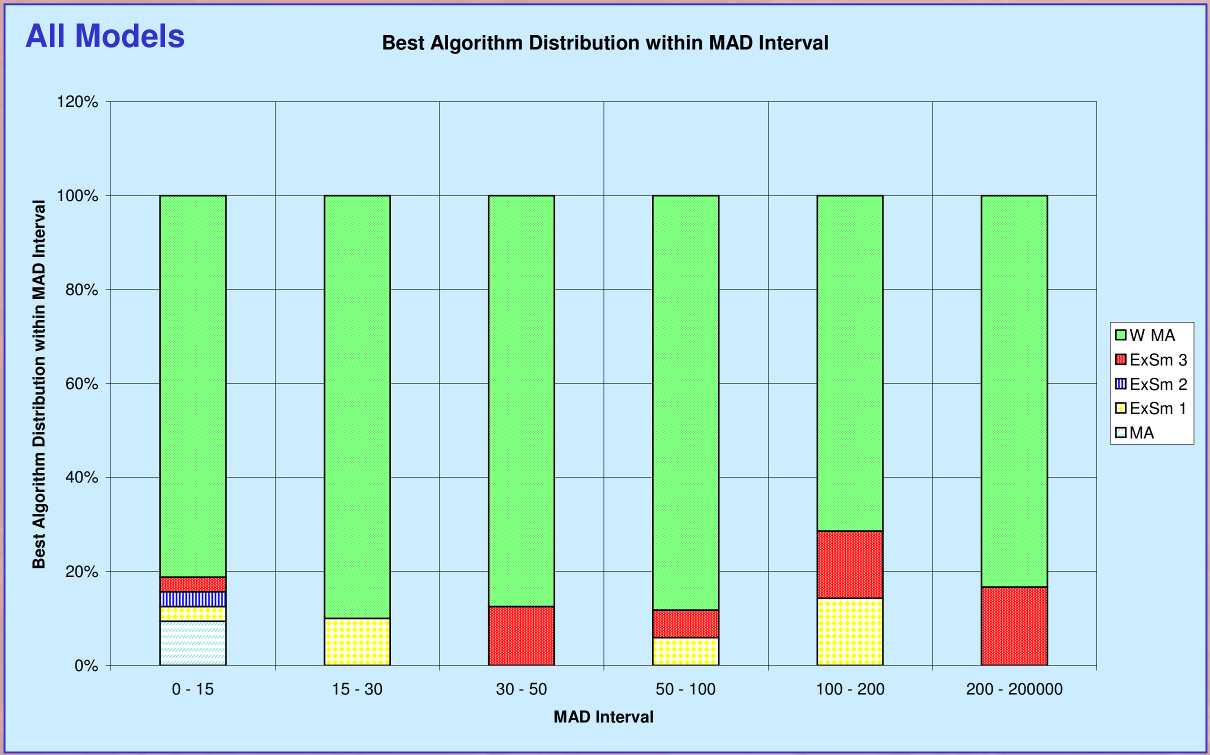


The graph shows that clustering items for Product Segment there are only few clusters with a M.A.D value over 300.



The analysis of the M.A.D. over the Future shows that the Weight Moving Average has more effect on the scenario, while Moving Average and Triple Smoothing has less influence in comparison with the previous case.

Suppliers Cluster Lead Time M.A.D.

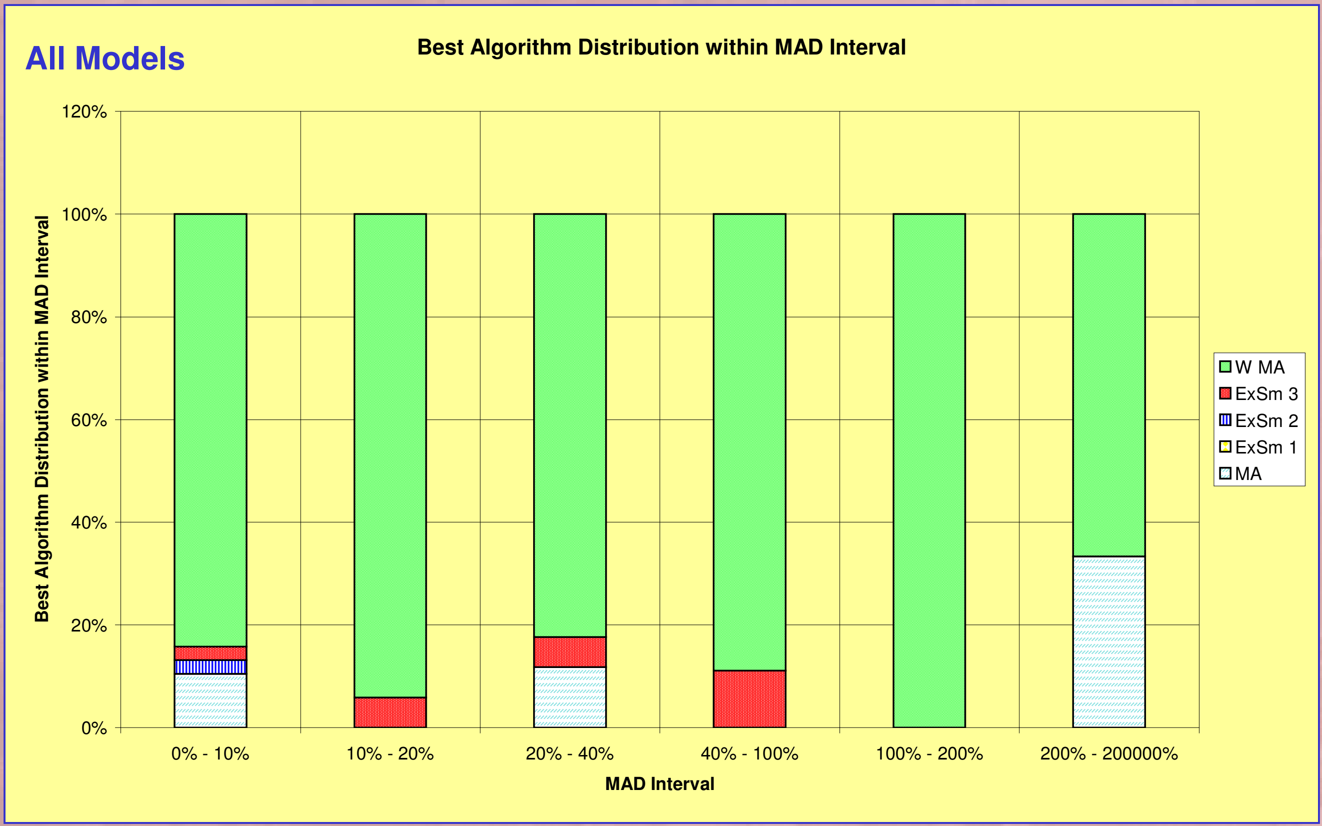


The Exp. Smoothing Algorithms have more effect on the scenario for high error values.

Any case The WMA Algorithm is the most robustness solution.

In order to use the WMA Algorithm the Suppliers clustering is not a good solution in comparison with other strategies.

Suppliers Cluster Future M.A.D.



In this analysis we can see a few influence of the Triple Exp. Smoothing and the Moving Average has good performance in the scenario for high error values.

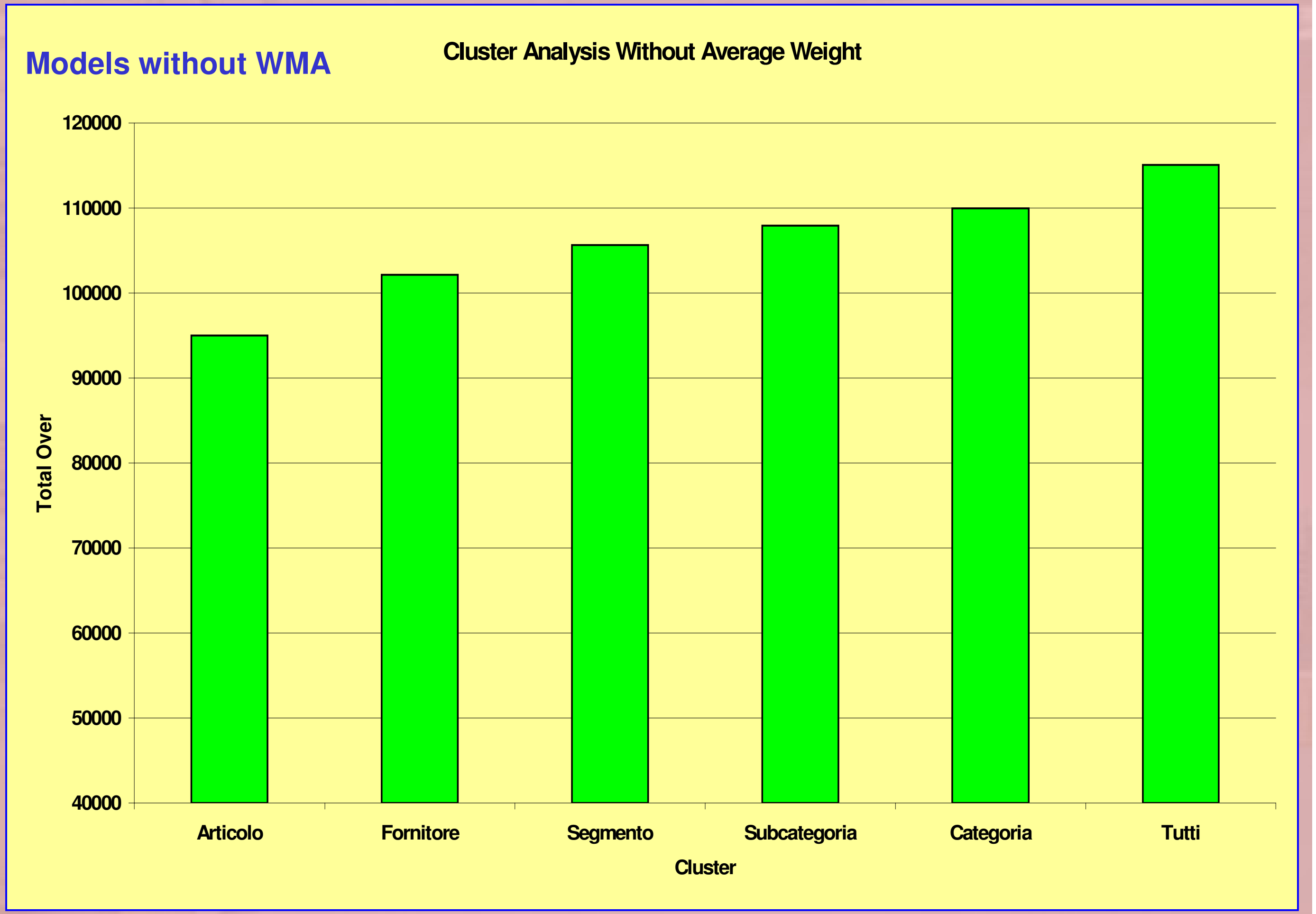
In the first M.A.D. interval we obtain similar results of the previous scenario, while the Weight Moving Average has more effect in the other intervals.

Clustering Analysis without Weighted Moving Average

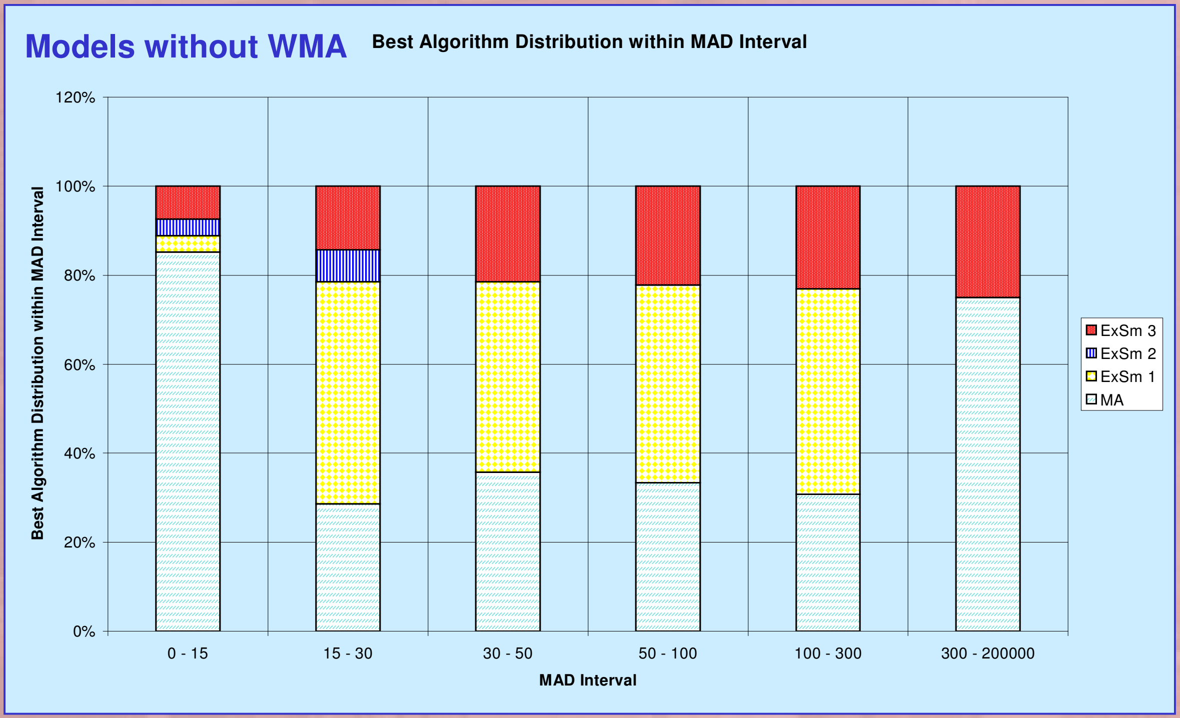
The analysis identifies that the Suppliers is the best cluster (not considering the Item one).

We can see that the other clusters have the same behavior of the previous analysis.

Only clustering items for suppliers shows better results then previous scenario.

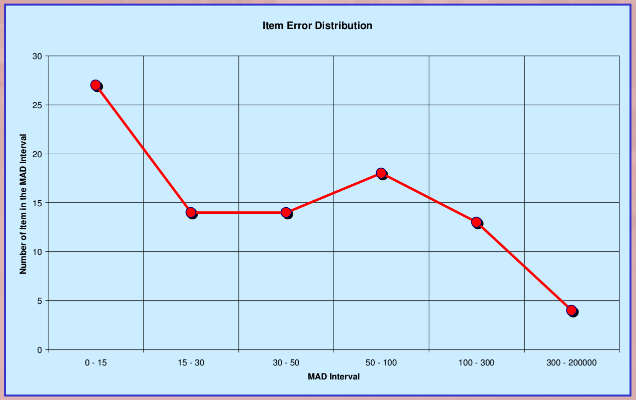


Suppliers Cluster Lead Time M.A.D.

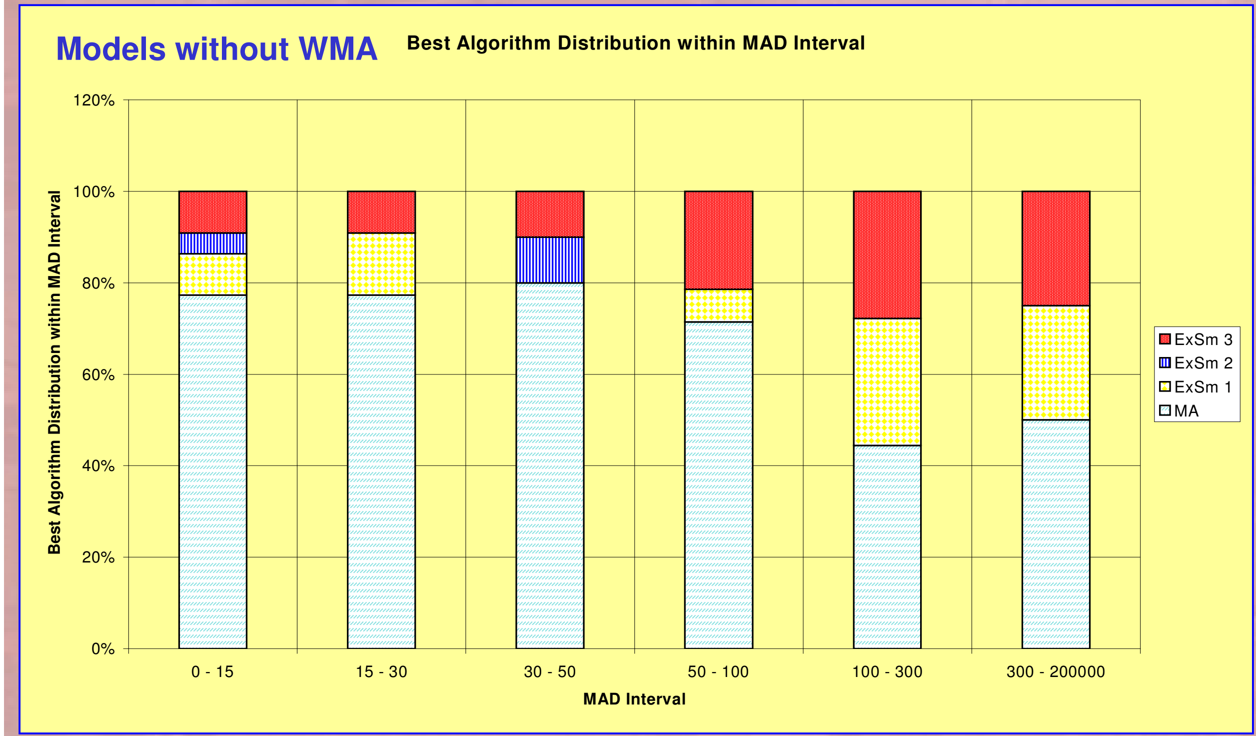


In this analysis we can see that Moving Average Model is the best even if The First and The Triple Exp. Smoothing are present.

In that case is clear how Moving Average Model is the best into little error interval. There is no best model for any other interval.



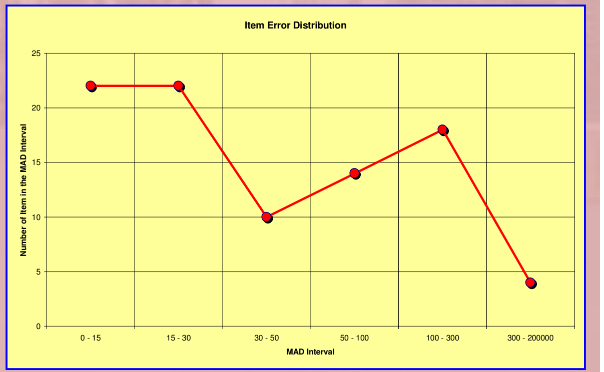
Suppliers Cluster Future M.A.D.



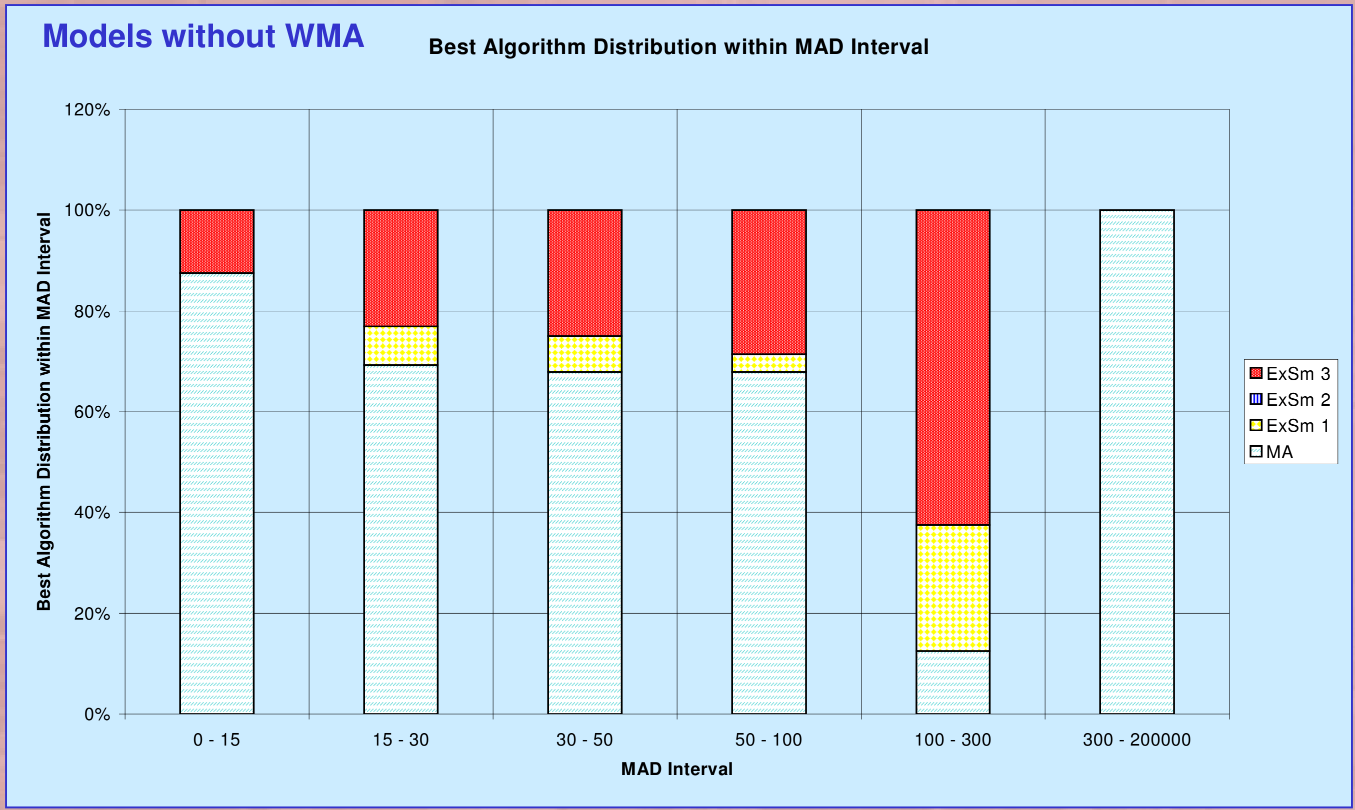
In the High M.A.D. Intervals the Exp. Sm. Algorithms have more influence.

Choosing this algorithm is a Risky Solution due to the high error values.

In a scenario Without Weighted Moving Average Algorithm the Moving Average has more influence.

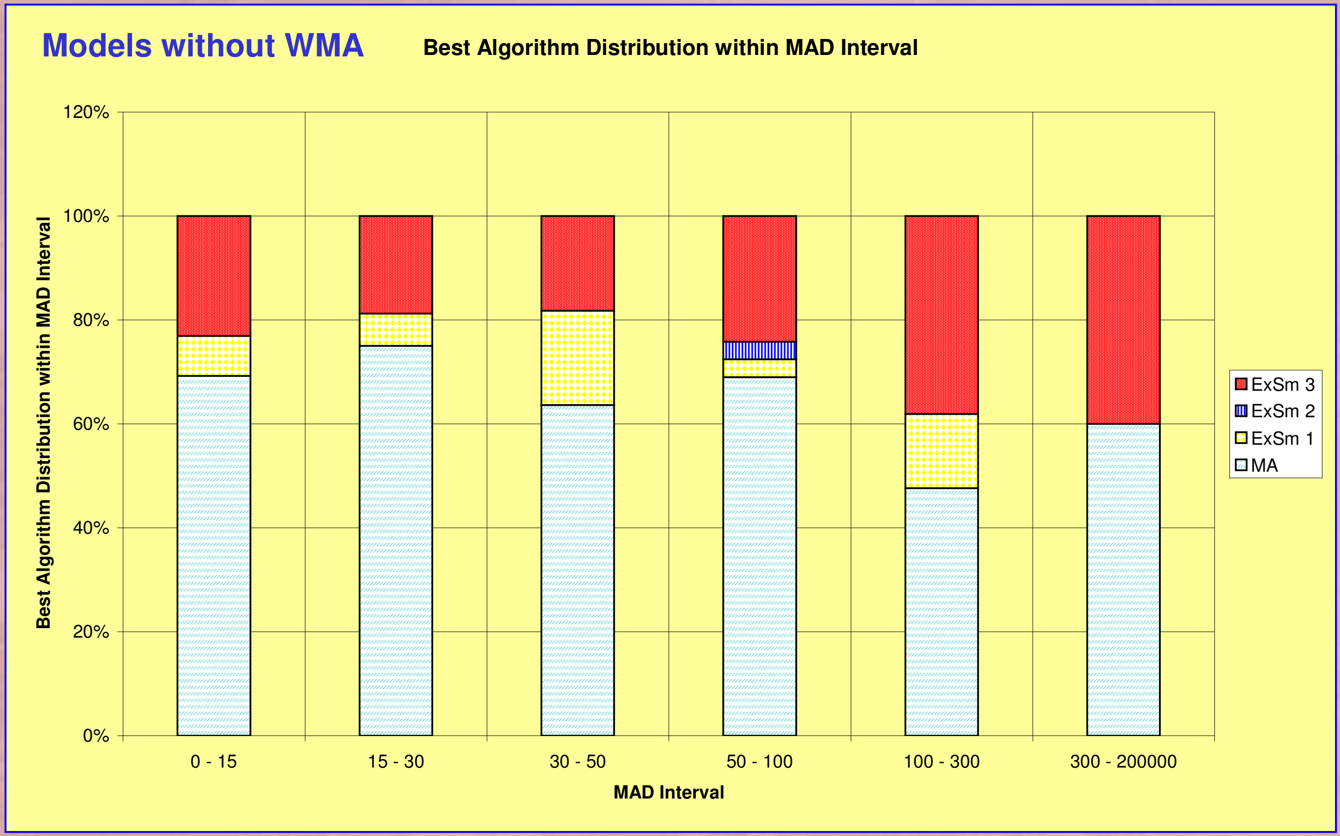


Product Segments Cluster Lead Time M.A.D.



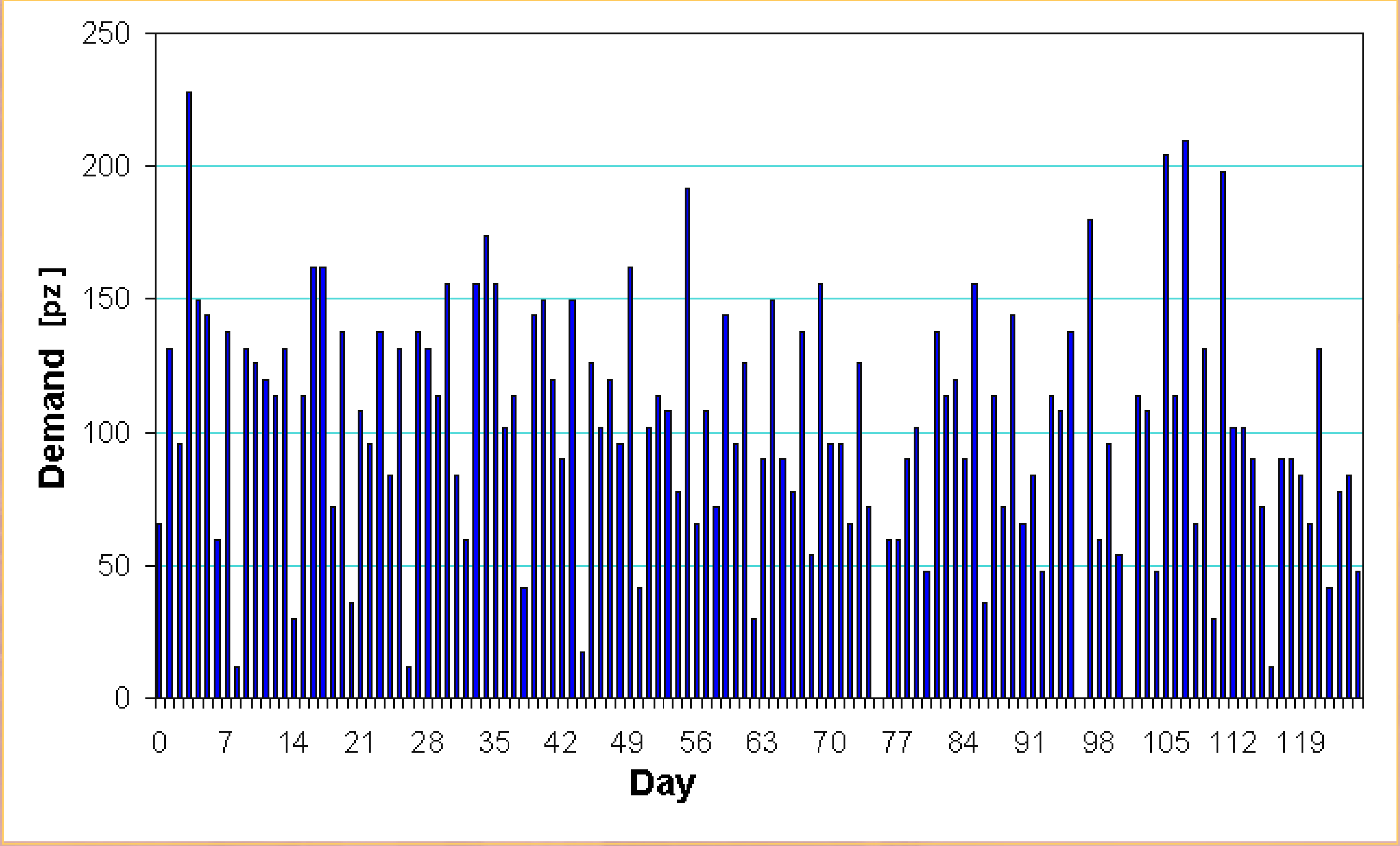
The Moving Average is the best model even in clustering items for product segment. The other significant model is the Triple Exp. Smoothing.

Product Segments Cluster Future M.A.D.



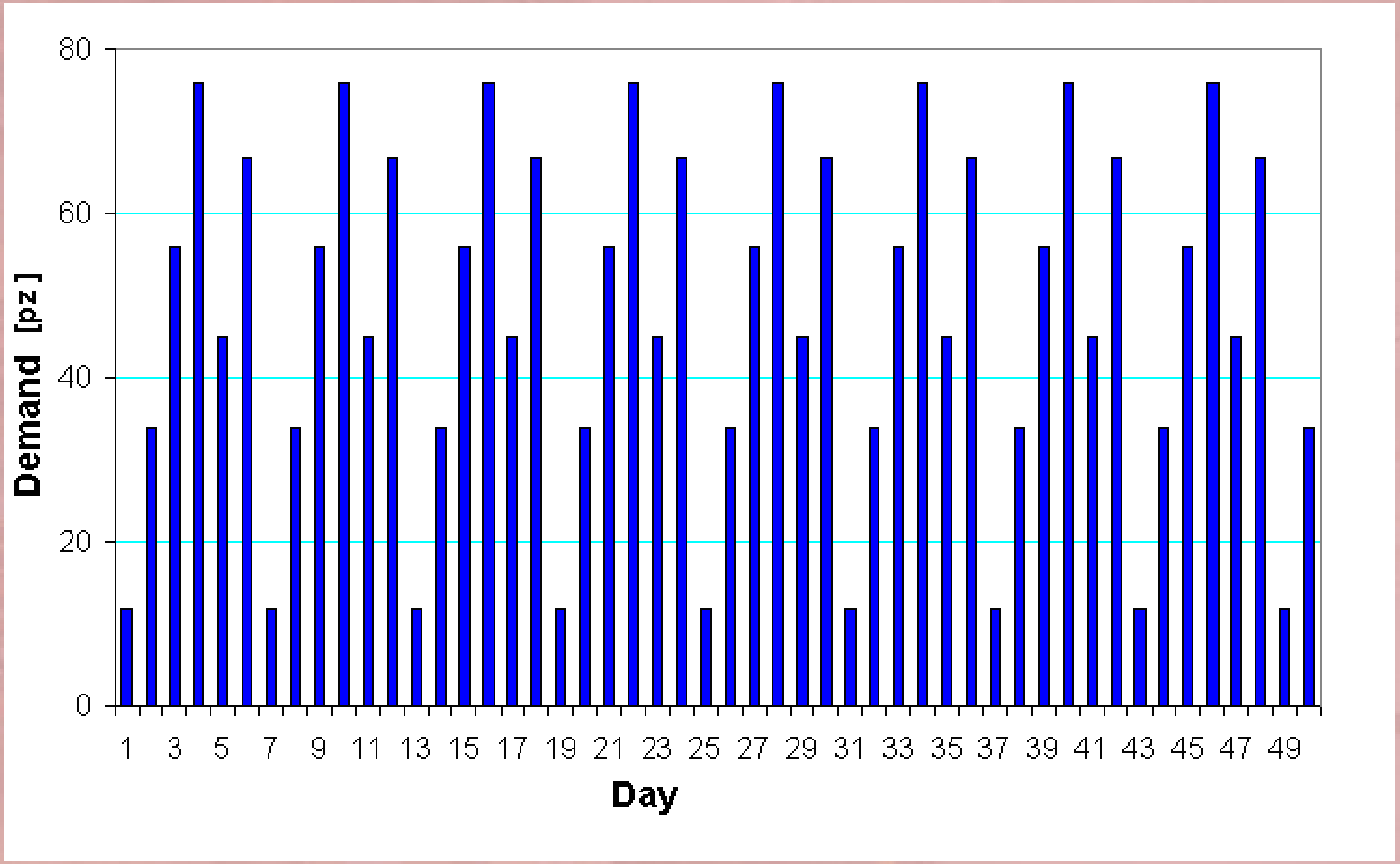
Even in this analysis the Moving Average Algorithm is the most significant.

Real Behavior



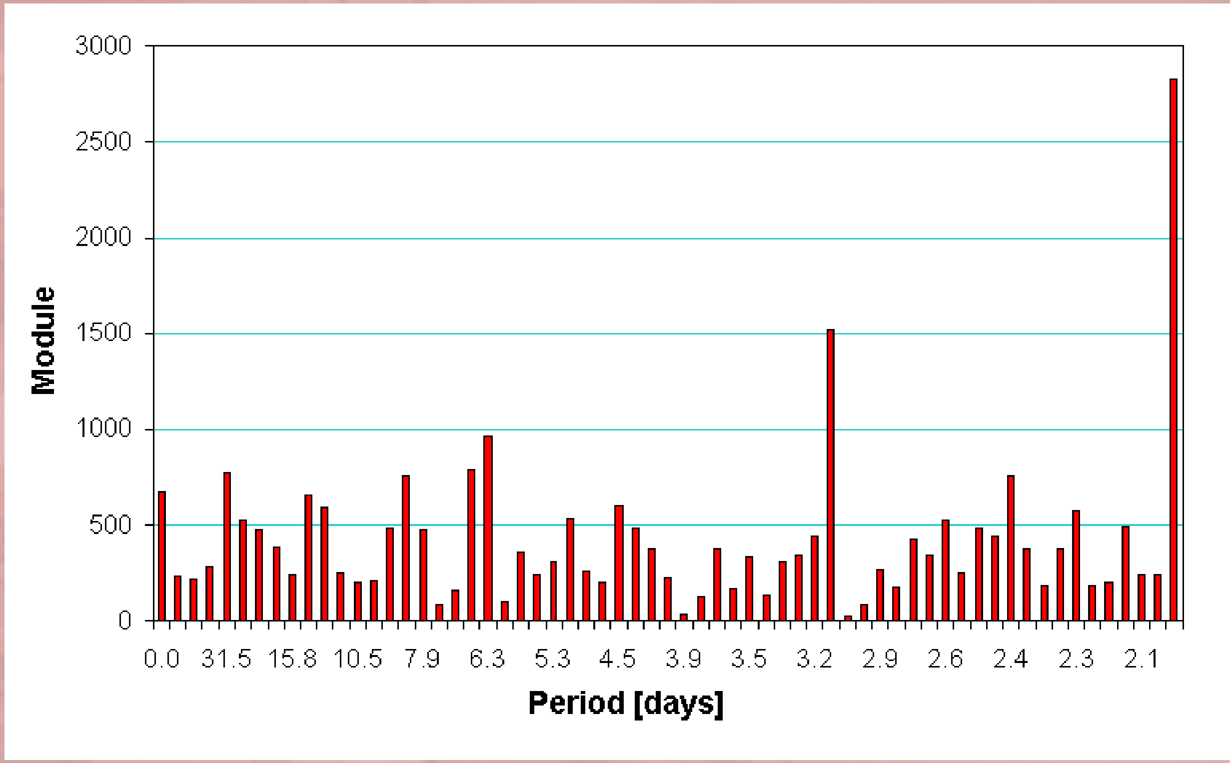
Demand: Real behavior

Theoric Behavior



Demand: theoretic behavior

Frequency Domain Methodology



Breaking down the initial signal into harmonics through DFT

Algorithms Synthesis

The applied technique was effective in making a quantitative determination of the periodicity value t of the demand to which to apply the 3rd Degree Exponential Smoothing.

Compared to other techniques used in the signal processing field (such as autocorrelation), the DFT can be utilized to highlight not only the predominant periodicity but also the modulus of each component of the initial signal.

Conclusions

- The paper proposes the use of simulation for tuning the management policies in supply chain management of retail stores in order to consider the complexity of the real system and impact of critical conditions.
- The case proposed represent a simplified realistic scenario, where just few factors affect the logistics, even with this configuration the complexity of the problem is evident as well as the effectiveness of the simulation approach.
- It is quite interesting to note that the different criteria, also if they could appear similar at a first look, provide quite different results that only simulation can quantify in term of profitability, efficiency and effectiveness in the specific scenario.