Simulation for Time Series Analysis & Forecasts

Agostino Bruzzone & Simone Simeoni

Liophant Simulation

agostino@itim.unige.it
simone.simeoni@liophant.org

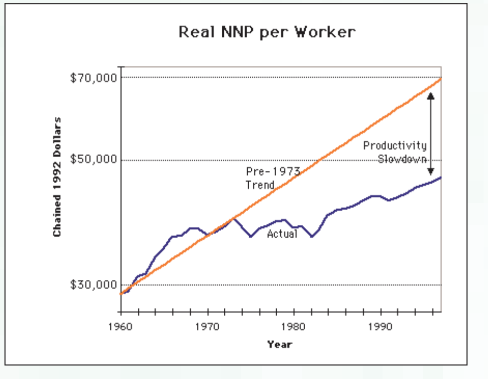
www.liophant.org

Tutorial Goals

- ✓ To identify Critical Issues in Forecasting
- ✓ To define M&S Potential in Testing Forecasting
- ✓ To introduce Forecast Algorithms
- ✓ To describe methodologies for Best Fitting of Forecast Algorithms
- ✓ Examples and Exercise in Logistics Networks

Forecasts

- ✓ Forecast is a statement of what is judged to happen in the future in connection with historical data.
- ✓ Forecast is what you expect to happen in the future.
- ✓ Forecasts must be Credible
- ✓ People need to Trust Forecasts for using these with success



Precision vs. Robustness

In Forecasting the Robustness is the most critical aspect in term of performance evaluation.
In this context, usually it is not important to have a high precision in forecasts if their robustness is still weak.

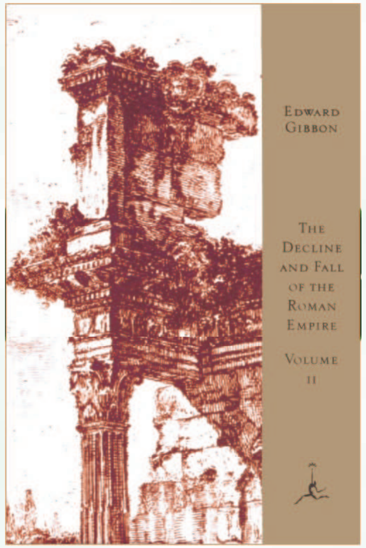
Robustness

the degree to which a system or component can function correctly in the presence of invalid inputs or stressful environment conditions

Institute of Electrical and Electronics Engineers. IEEE Standard Computer Dictionary: A Compilation of IEEE Standard Computer Glossaries. New York, NY: 1990.

Predicting the Past and Predicting the Future

The forecast methodologies use historical data to make assumption about what will happen, but it is really critical for them to predict major scenario changes.



In this context it is critical to check if:

The past can predict the future ?!

Often it is necessary the human support to analyze and note the market scenario, because the assumption that was true yesterday will be true tomorrow not ever works.

Forecasting Company Examples

Goodyear implemented a demand forecasting system in mid-2000 but hasn't shown significant improvement in managing inventory and in the last year tire lost more money then the years ago.

Nike implemented a demand forecasting (i2) in June 2000 and nine month later its executives acknowledged that they would be taking a major inventory write-off because the forecasts from the automated system had been so inaccurate.

Forecasting Systems Highlights

- ✓ Forecasting systems are only as good as the data put in.
- ✓ Software can't predict the future, particularly sudden, unexpected shifts in economic or market conditions.
- ✓ Forecasts sometime affect the System Evolution

“ ...I would say that if you looked at the split between people, science and process, people are half the equation. Algorithms are algorithms. That is not what will win the game for me." Sumatra Sengupta CIO for Scotts Co.
1.8 Billion USD revenues in 2003, Lawn & Garden Care products

"Anyone who thinks you can do it with just mathematics and statistics is only partly right. Human intelligence is also required." Doug Richardson, CIO of Vicor,
150million USD revenues in 2003, managing 1.7trillionUSD transactions over internet

Forecasting Systems Investments

In 2002 alone, companies spent $19 billion on demand forecasting software and other supply chain solutions. IDC

IDC Analyze the Future

In a survey of 196 senior executives, 45 percent said that supply chain technology in general had failed to meet their expectations.

CIO

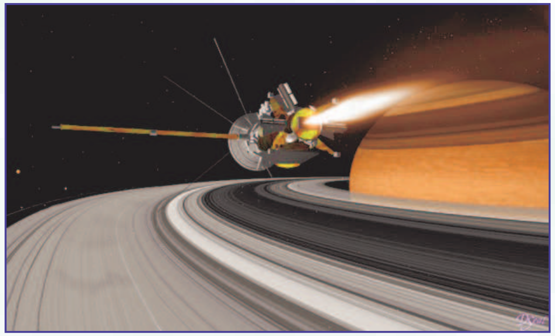
Crystal Ball vs. Forecasts

- ✓ Crystal Ball don’t Exist
- ✓ Forecasts are not Point Values but Confidence Regions
- ✓ Reliability, Fidelity and Precision of Forecasts need to be investigated during Analysis
- ✓ Sometime Reality is Unpredictable
- ✓ Predictability needs to be referred the specific Problem
- ✓ Good demand forecasting requires a combination of accurate data and smart people.

Advanced Techniques

Advanced Techniques can be used in order to provide significant improvements in forecasts performances; among the others

- ✓Artificial Neural Networks (ANN)
- ✓Fuzzy Logic
- ✓Knowledge Based System KBS
- ✓Genetic Algorithms
- ✓Data Fusion



However

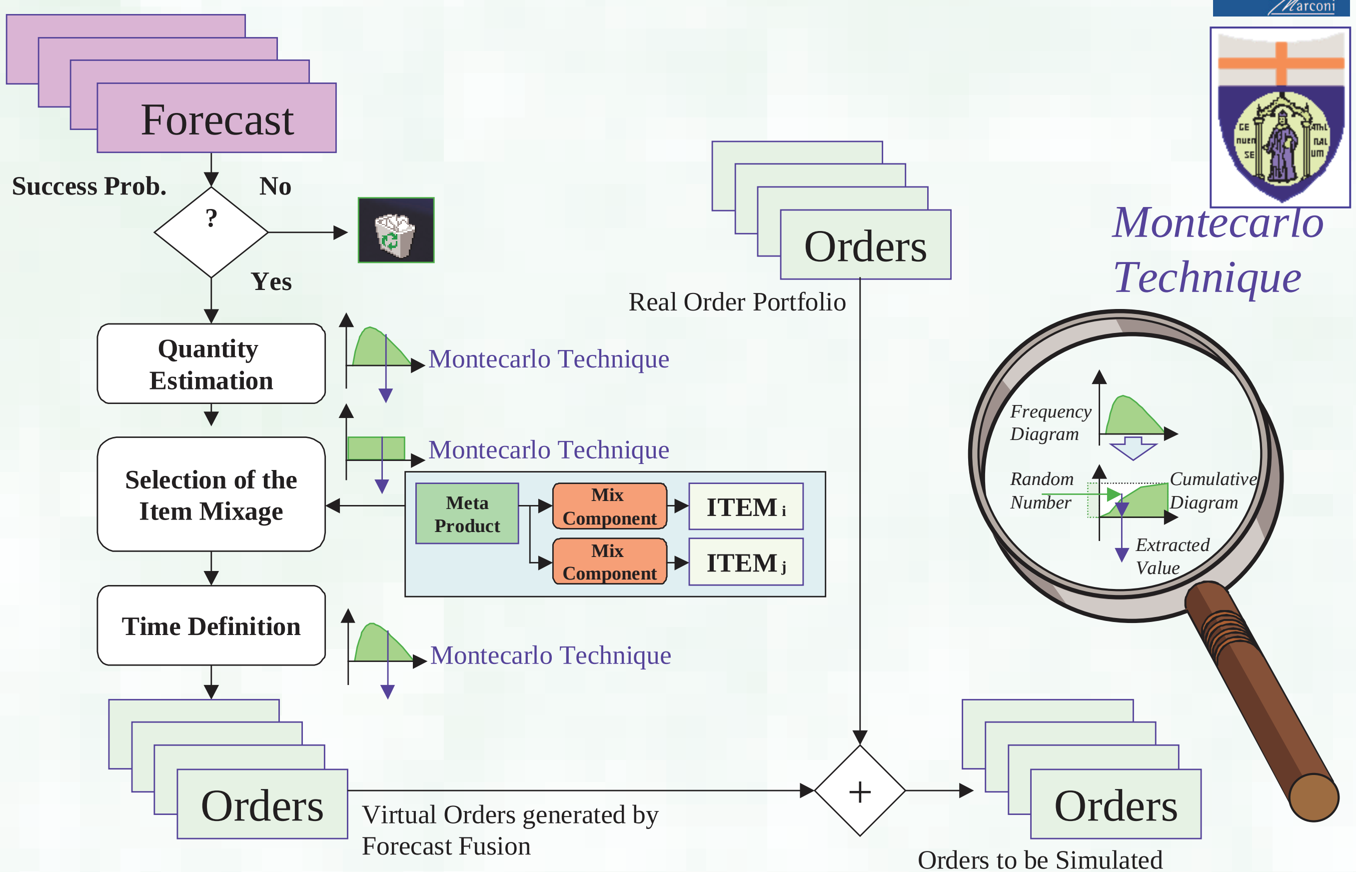
- ✓ New Forecasts Techniques don’t change the Real System Predictability

or

- ✓ New Forecasts Techniques can’t overpass traditional methods and become a Crystal Ball

Data Fusion & Forecasting

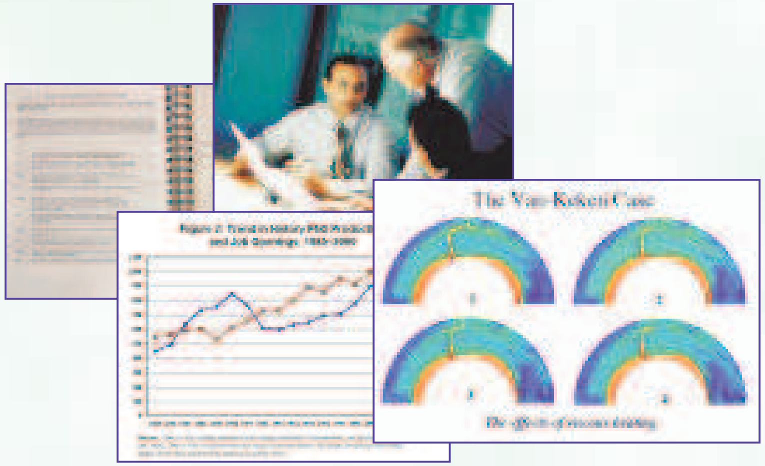
✓ Most Promising advances in Forecasting are related to merging information techniques devoted to improve their reliability (Data Fusion, Fuzzy Logic)



Simulation & Forecasts

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

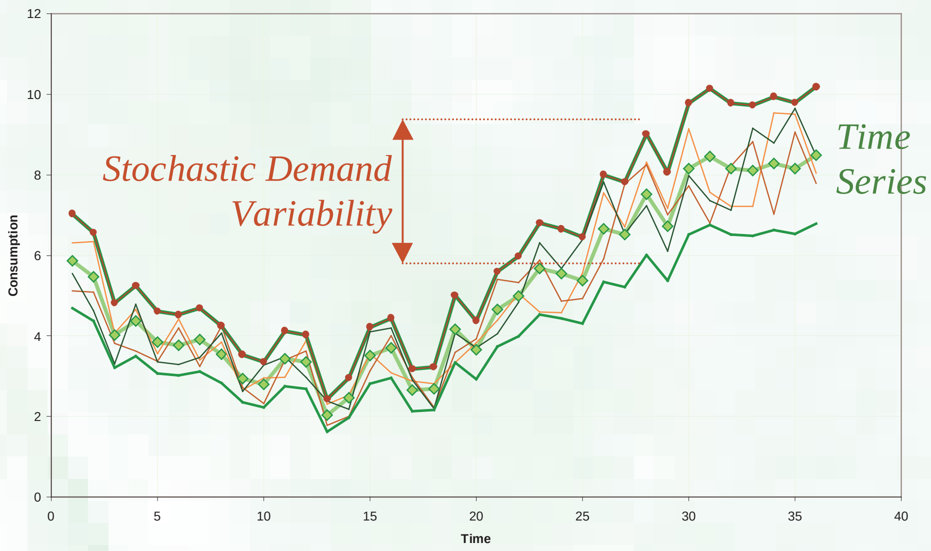
Historical Data
Expert Estimation
Phenomena Symptoms
Boundary Conditions



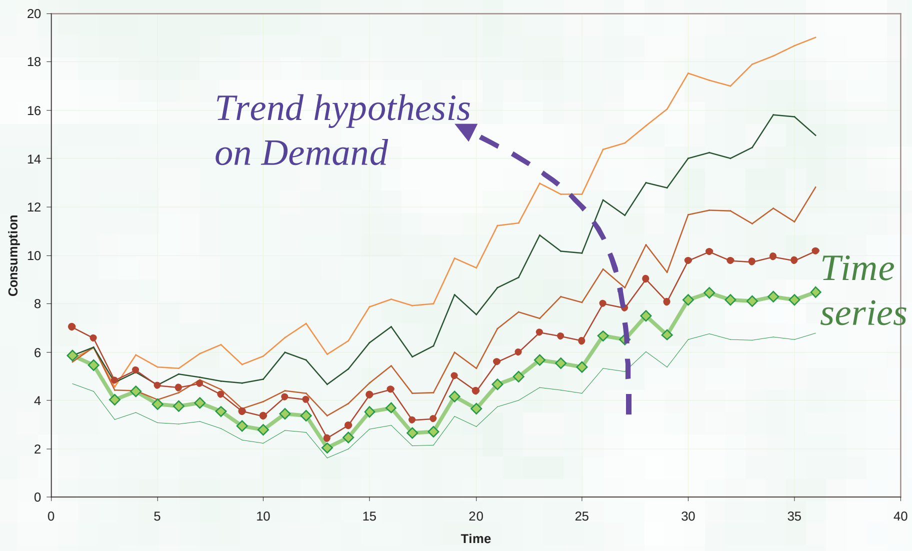
Modeling & Simulation can be used for testing Forecasting Techniques and for Measuring their Performances over complex scenarios

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 Costs

- ✓ Management that not pays attention to forecasting assumes that what will happen in the future is the same to what has happened in the past.
- ✓ An inadequate forecasting increase:
  - ✓ Work
  - ✓ Materials
  - ✓ Costs (Expediting or Stock - Out ones)
- ✓ Increasing forecasting we increase cost of collecting and analyzing data.
- ✓ The optimal level cost of forecasting implies the balance of the aspects above.

Generic Models

- ✓ ARIMA (Autoregressive Integrated Moving Average) was introduced by Box and Jenkins in 1970, who supposed to eliminate the trend and seasonal component in a time series by differencing.
- ✓ ARMA (Autoregressive Moving Average) models a time series that was eliminated trend and seasonal components by differencing.
- ✓ ARMAX (Autoregressive Integrated Moving Average with exogenous input) introduced by Box and Tiao in 1976 consider the influence of exogenous variable on the output variable of interest.

State Space Methods

- ✓ The State Space Method model separately each term of a time series 0bservation as :
  - ✓Trend Term
  - ✓Seasonal Term
  - ✓Regression Term
  - ✓Disturbance Term
- ✓ The State Space Method puts together each models of components in order to obtain a single model for time series analysis.
- ✓ The State Space began in 1960 with Kalman.

Forecasting in Logistics

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

-Estimate the Customer Demand

-Estimates Market Evolution

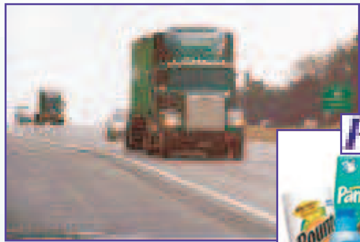
-Support Inventory Management

-Support Production Planning

Logistics & Forecasts

In logistics forecasting is really important to predict the future demand.

In this scenario is really important to determinate where to get the data for the forecasts for the different actors involved in supply chain.



As a study of Procter & Gamble
the further away your data is from the point of sale, the more data accuracy decreased and forecasting errors increases .

In logistic forecasting is necessary use point of sale formation to directly from the retailer to avoid overforecasting demand.

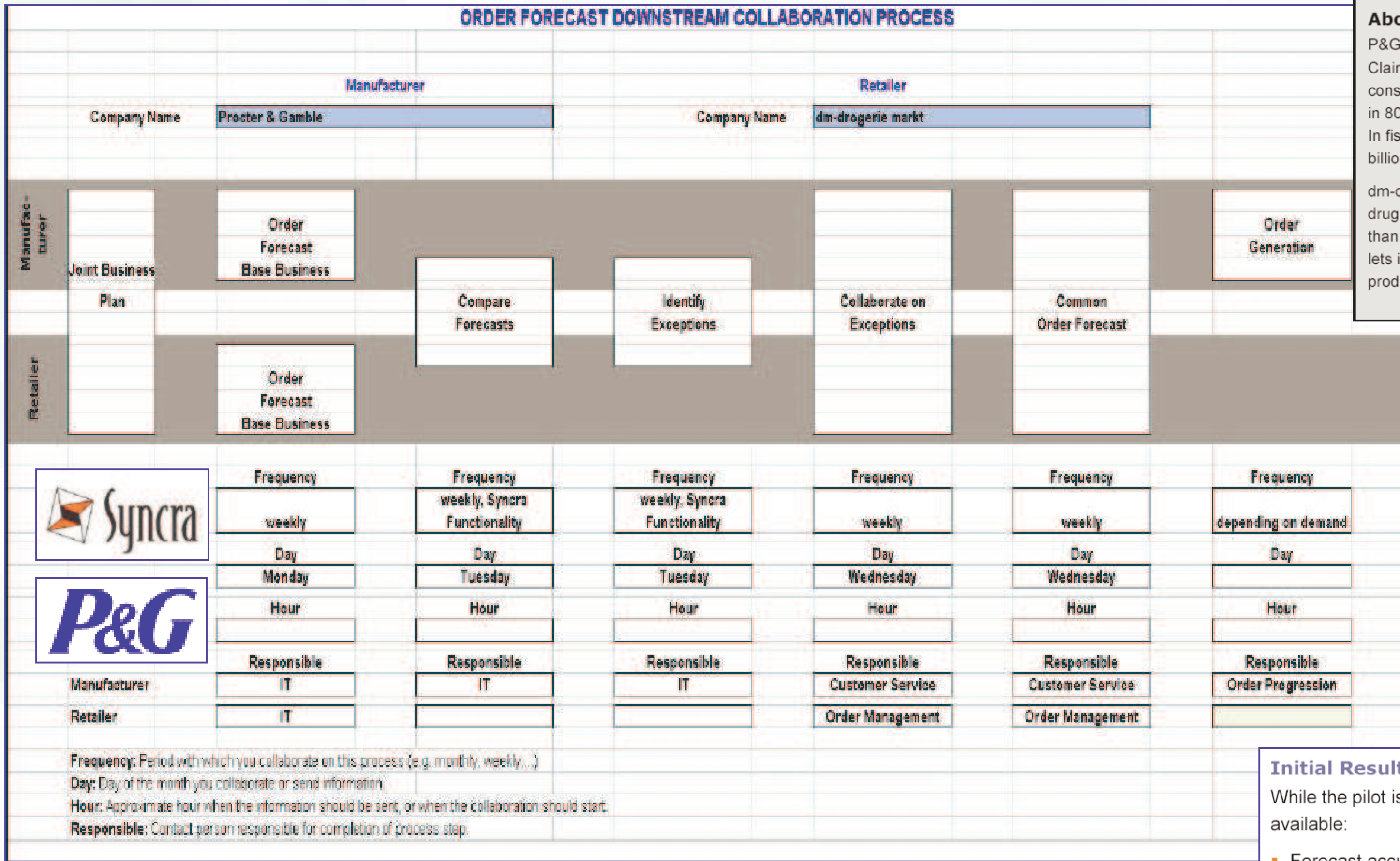
Supply Chain & Forecasts

Demand Forecasts are a particularly important piece of information within a supply chain.

- **Each level of a supply chain makes decisions that have ramifications throughout the entire system.**
- **The quality of a given decision depends on what the decision maker knows.**
- **As a result, the dissemination of accurate information is critical for the supply chain to operate effectively.**
- **Credibility is a key factor in the exchange of information: Will and should the receiver of information trust the veracity of the reported information.**
- **While credibility is easily established in some cases, it is often more elusive.**
- **This is especially true when the informed party has an incentive to distort her message to influence the receiver's actions.**

Gérard P. Cachon, The Wharton School, University of Pennsylvania,
Martin A. Lariviere, Kellogg Graduate School of Management, Northwestern University

Example of CPFR



About P&G and dm-drogerie markt:
P&G markets more than 250 brands, such as Bounty, Clairol, Ivory, Noxzema, Pampers, to nearly five billion consumers in more than 130 countries. With operations in 80 countries, P&G employs more than 106,000 people. In fiscal year 2001-02, the company's sales were $40.4 billion.

dm-drogerie markt GmbH + Co. KG is the second largest drugstore chain in Germany. The company has more than 14,000 employees working at more than 1,300 outlets in Europe, including 620 outlets in Germany. Their product line includes 13,000 SKUs.

CPFTR Syncra for P&G 2004

Initial Results
While the pilot is still running, initial results are already available:

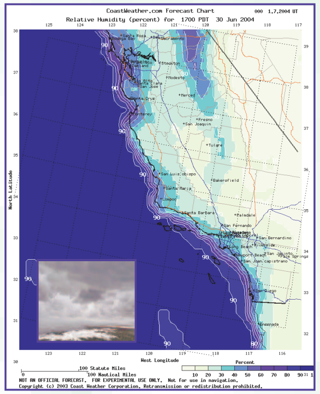
- Forecast accuracy of the second promotion compared to the first was up by 10 percentage points.
- Product availability during the second promotion at the outlet level increased by 4 percentage points.
- Statistical forecast error for the base business was reduced by nearly 50 percent through August.

Collaborative Planning, Forecasting and Replenishment

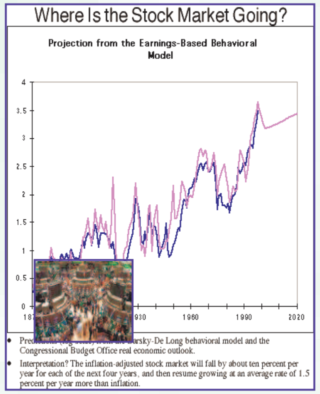
Applications for Forecasting

To Forecasts the Future Forecasting Algorithms are requested. Many different applications (Weather, Economics, Logistics, etc.)

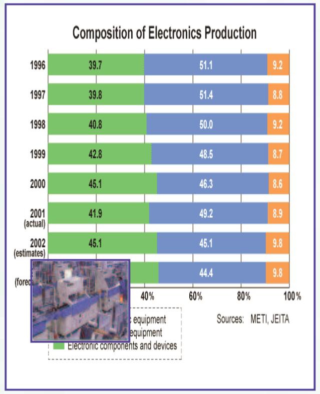
First Order Exponential Smoothing in 1944 was Implemented by Brown and It was promoted and used in 1959/1962



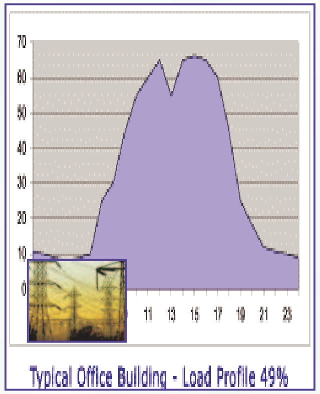
Weather



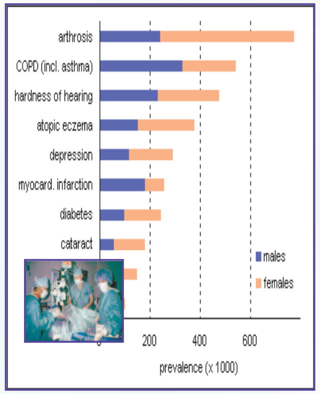
Market



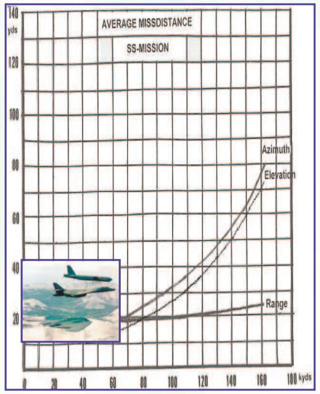
Logistics



Power



Medicine



Military

There are several Forecast Algorithms types, many of them are customizable, but in the developing phase for all of them the setting is a really critical issue.

Algorithm Efficiency

The Forecast Algorithm effectiveness has to be measured on statistic benefits in a medium long scenario not on the precision on a single point

To use correctly a forecast algorithm is necessary to consider:

- Implementation Methodologies

-Algorithm Robustness

-Management and Procedure consolidation

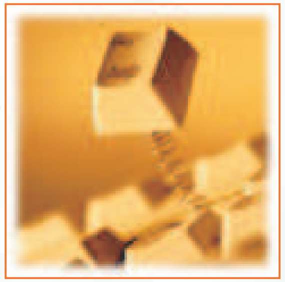
-Parameter Proper Setting

Performance/Process Control

Considering the scenario stochastic nature and variability it is really important to guarantee a Control System for the Performance and for the Process.

The Control System has to verify and correct Forecast System Settings:

- **To develop correct time series analysis and synthesis (i.e. Representative Samples, various mix, errors/ periods with not representative consumption)**
- **To estimate Costs, Benefits and Risks of different Policies (i.e. Warehouse Costs, Stock-Out Risks, Service Quality)**
- **To develop a forecasting system easy to manage and to maintain (i.e. fitting of forecast algorithm)**
- **To set an implementing plan in order to control the advancement**
- **To measure Performances and critic event**
- **To control the Start - Up and the operative management**



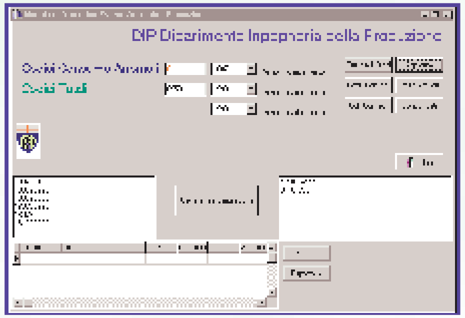
Algorithm’s Selection

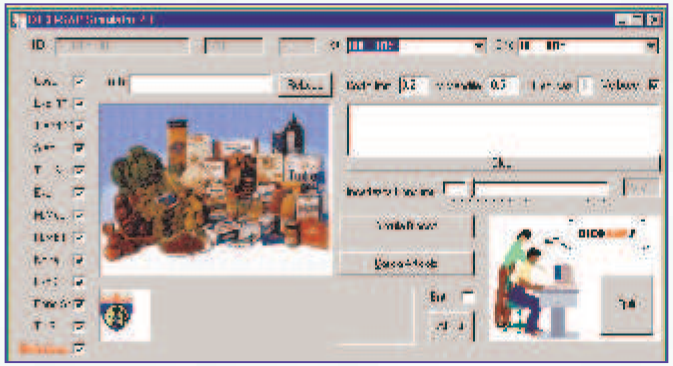
In a case study in partnership with one of the most important Italian Logistic Company that was implementing a new ERP System we used DICOSAP Simulator in order to to select the Robustness Algorithm and the parameter setting .

In the specific we used:

- A time series Analyzer in order to detect errors/ periods with not representative consumption

- A simulator to select the best algorithm and the parameter settings





DICOSAP

Depots & Inventory Clustering Optimal Setting, Analysis & Planning

Fit the parameters of each forecast algorithms

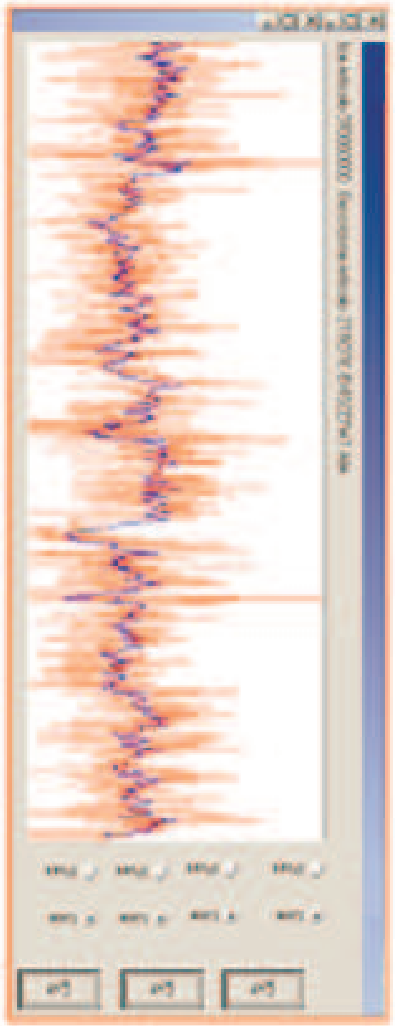
Choose the best algorithms

Define the best algorithm and fit the parameters for different clustering

Simulate stochastically the time series to estimate robustness of algorithms

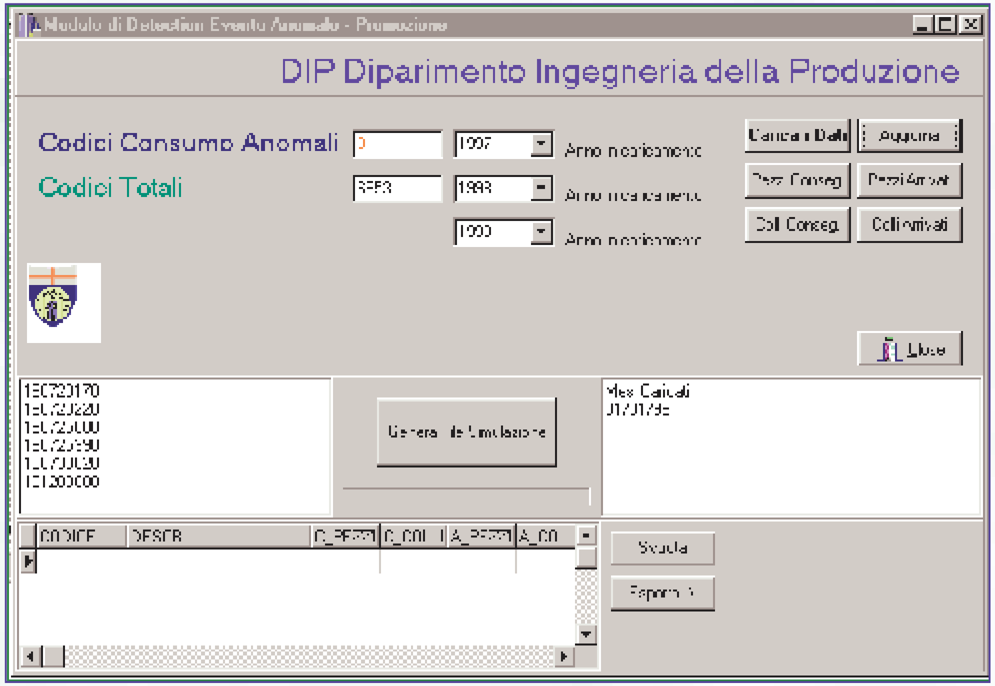
test the results on n-replications

Define the seasonal period on time series



Not representative event's Detection

To analyze the effect of promotional policies on the central warehouse, we use model in order to collect all the historical data about the Departures and the Arrivals flows and to analyze them.



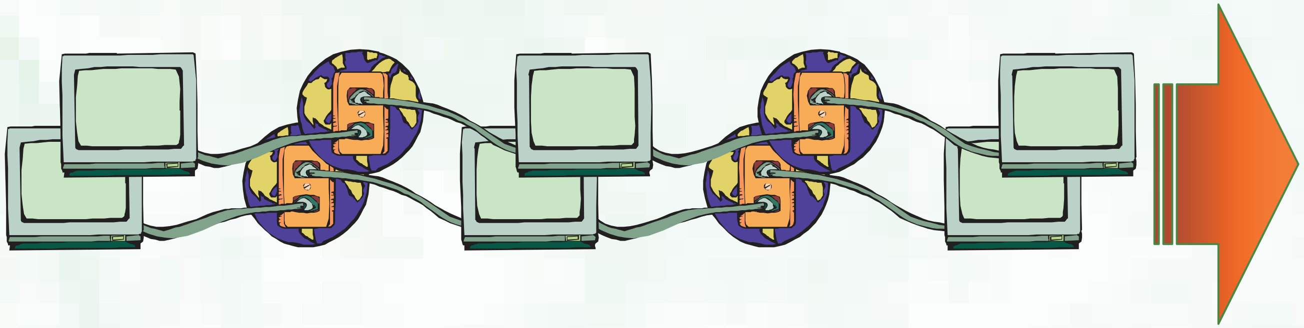
The Model consider inventory management hypothesis on different scenarios, with days and/or week periods, cutting off the events related to values not compatible in a statistic way with the time series and evaluating the variance on stochastic factor with Montecarlo techniques.

Input Importance

The affordability and the coherence of the inputs are important issues to carry out a good forecast.

<u>The DICOSAP Simulator was used over a Retail Case Study for:</u>

- *<u>Elaborating</u>* the consumption historical data of over 15,000 items in a 48 months scenario
- *<u>Optimal Best Fitting</u>* for the parameters ha of 15 algorithms
- *<u>Optimal Algorithm Identification</u>* for each item for week/day scenarios



Total elaborating time: 3 days on 33 computers in a local LAN

DICOSAP Simulator

❖Item

❖Supplier

❖Lead Time

❖Safety Stock

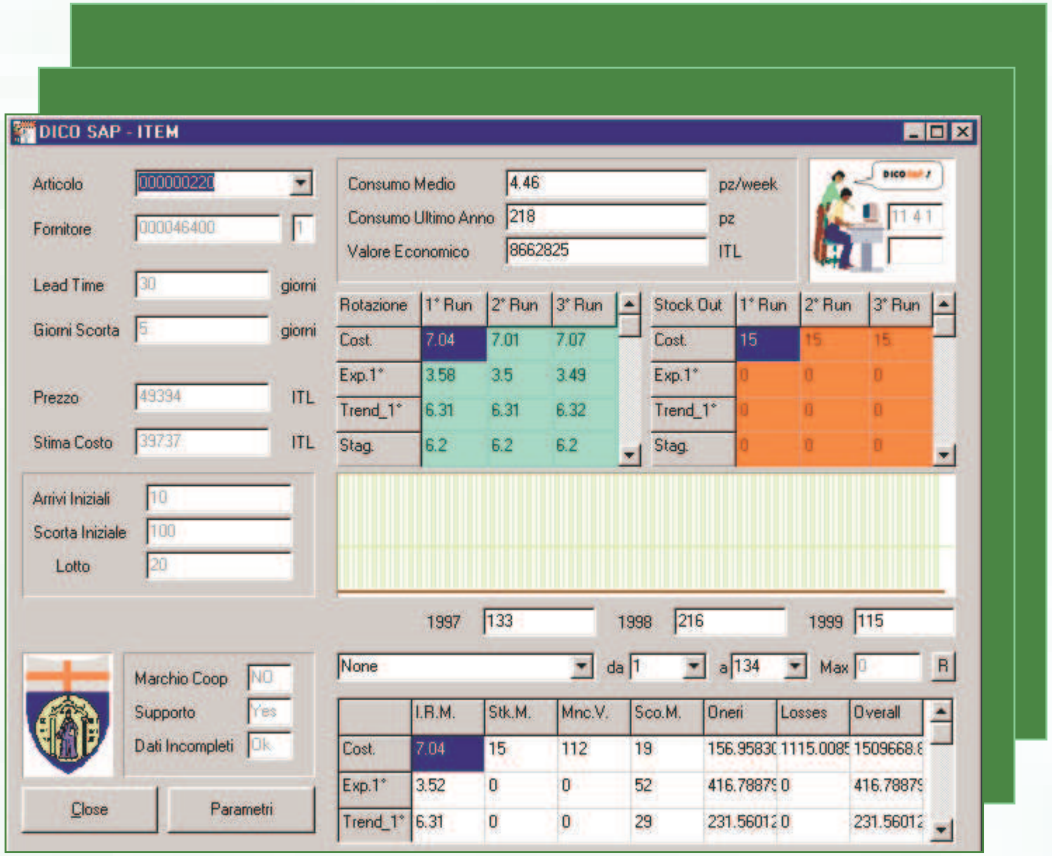
❖Stock -Out Number

❖Rotation Index

❖*Overall*

❖Best Supply Policy

❖Parameter Fitting of the selected algorithm



Evaluation Criteria

OVERALL: **is the measure of the algorithm excellence considering the warehouse fees and stock - out costs with appropriate weight.**

$$WarehouseFees = \sum_{i=1}^{Np} \sum_{t=0}^{Tf} \frac{coeff\_fees_i}{Tf} InventoryLevel_i(t) + HandlingCost_i \cdot Operazions_i(t)$$

$$StockoutCosts = \sum_{i=1}^{Np} \sum_{t=0}^{Tf} SalePrice_i \cdot (Demand_i(t) - InventoryLevel_i(t))$$

$$Overall = \sum_{i=1}^{Np} WarehouseFees_i \cdot Fees\_WeightFactor + StockoutCost_i \cdot Stockout\_WeightFactor$$

In the case of critical products, the strategic importance define that Stockout and Warehouse Weights Factors; usually Stockout is more important then Fees.

Parameter Fitting

For each item, the parameters of every algorithms are visible in a window or in a file. In the output there are safety stock level, and the coefficient and parameter values.

Parametri Algoritmi

	Pt.Med.	Coeff.1	Coeff.2	Coeff.3	Coeff.4	Coeff.5	Coeff.6	Coeff.7	Coeff.8	Coeff.9	Coeff.10	Giorni
Cost.												42
Exp.1°	0.899999											49
Trend_1°	12											49
Stag.	3											42
#Tr._&_S	7											49
Esterno												42
M.Mob.	12											49
M.Mob.P.	10	0.341417	0.170708	0.113805	0.085354	0.068283	0.056902	0.048773	0.042677	0.037935	0.034141	49
Niente												42
Exp.2°	0.600000											49
Trend_2°	12											49
Pond.St.	2	2	0.899999									42

Aggiorna Chiudi

Using automatic optimization methodologies the model select the most robust algorithm.

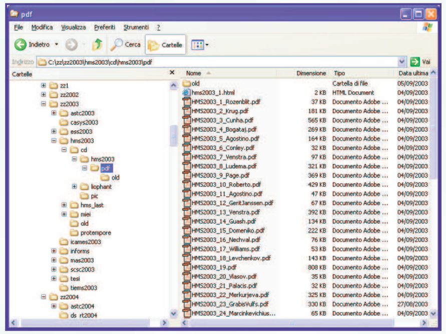
DICOSAP Outputs

ALGO: File with the best algorithm and its parameter fitting

SIMUL: File with simulation results in term of consumption, economic quantification , rotation index, stock -out for each simulation run

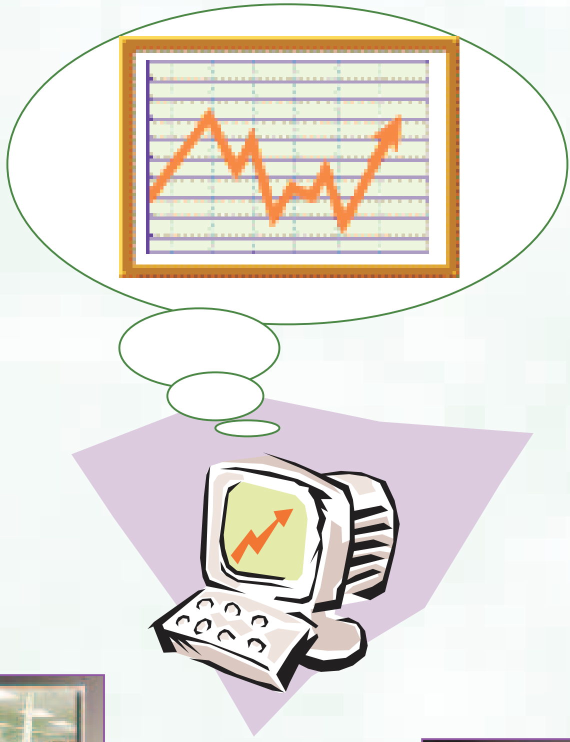
SUMMA: file with season period, the consumption with a short/long scenario,quantification of fees, stockout and overall

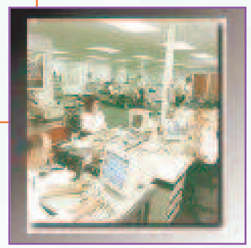
For each item simulator analyses all data.



Forecast Algorithm Examples

- Moving Average
- Weighted Moving Average
- Single Exp. Smoothing
- Double Exp. Smoothing
- Triple Exp. Smoothing



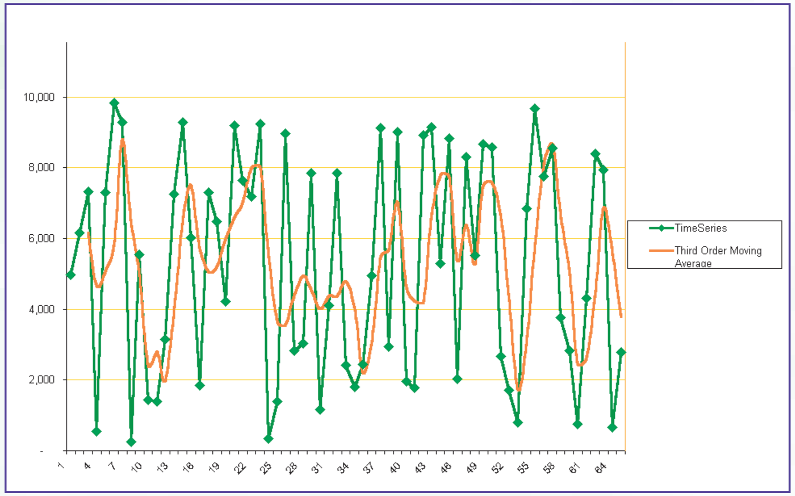


Moving Average Algorithm

The Moving Average consider a time series before the period to predict and use the historical data to carry out the forecast for the next period.

$$P_{t+1} = \frac{1}{k} \sum_{i=t-k+1}^{t} y_i$$

Order = number of periods



For each forecasting step the Moving Average consider the last historical data and delete the oldest one, calculating the new of average on the new time series.

This algorithm allow to smooth the irregular behavior on time series.

Weighted Moving Average

This algorithm use the same principle of the simple Moving Average , The Weighted Moving Average introduce weighting factors for each historical data.

Typically, the weights are decreasing for the most remote data. In this algorithm the more weight is assigned to more recent data.

Otherwise it is possible use different criteria to attribute the weight (i.e. seasonal).

$$F_{t+1} = A_t(n) = \sum_{i=t-n+1}^{t} w_i \cdot D_i = w_{t-n+1} \cdot D_{t-n+1} + w_{t-n+2} \cdot D_{t-n+2} + \cdots + w_t \cdot D_t$$

t.c. $\sum w_i = 1$

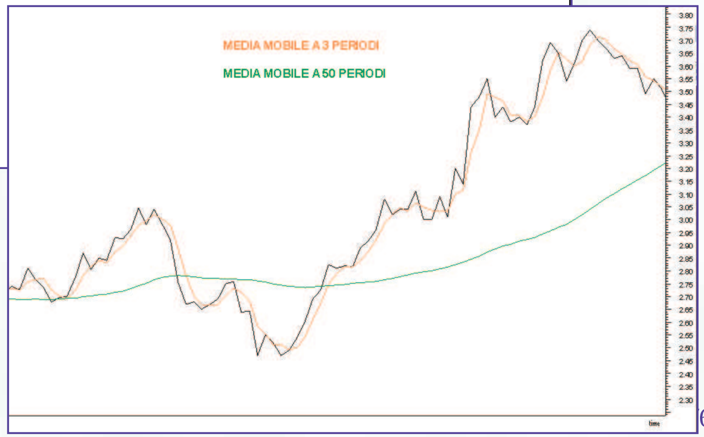
$WMA(3) = P_{t+1} = p_1(X_t) + p_2(X_{t-1}) + p_3(X_{t-2})$

Third Order Weighted Moving Average

p_i = weight

P_{t+1} = forecast

X_t = time series



Single Exp. Smoothing

The most fundamental aspect for this algorithm is the recent time series give a best support to make assumption on the future behavior. Using this algorithm it is possible reduce the number of necessary data for forecasting ad so reduce the database size.

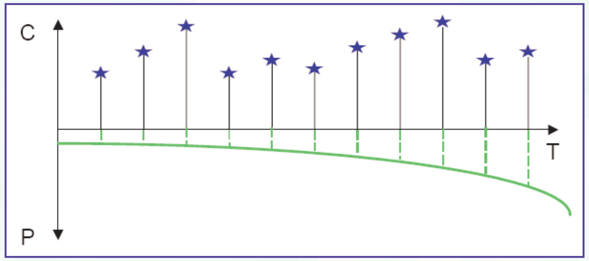
$$P_{t+1} = f(P_t X_t) = \alpha X_t + (1-\alpha) P_t$$

P= Forecast

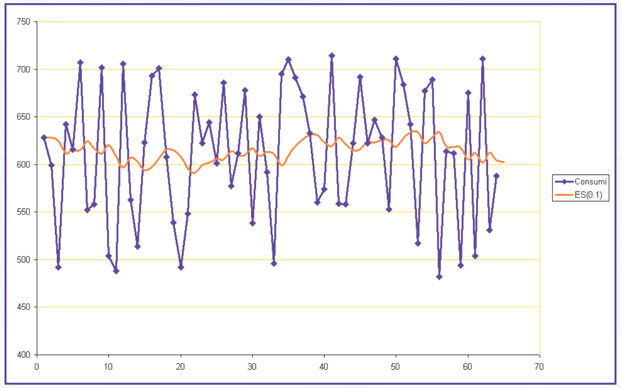
X=Time Series

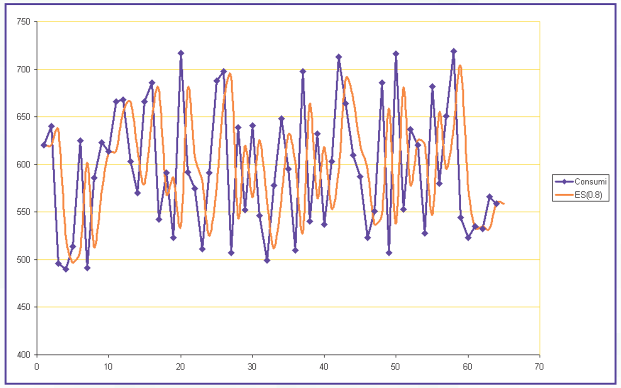
$$0 \le \alpha \le 1$$

High values of α means a major weight attributed to time series



Low α Value





High α Value

Double Exp. Smoothing

The Double Exponential Smoothing use two coefficients α e β, making forecasts in two steps: a Basic Value (S_t) and a Trend Value (G_t), in order to consider also trend effects.

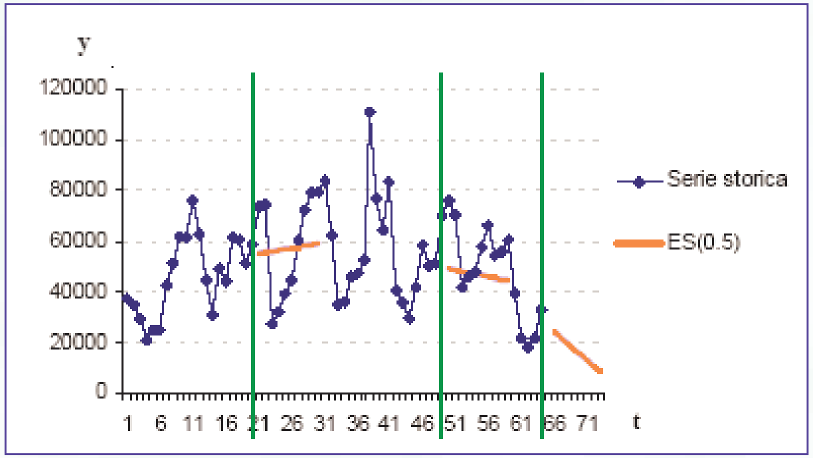
$$P_{t,t+\tau} = S_t + \tau G_t$$

τ = interval time

S_1 e G_1 can be estimated on the time series or using regression methodology. The α e β factors can be optimized using algorithms.

$$S_t = \alpha X_t + (1-\alpha)(S_{t-1} + G_{t-1})$$

$$G_t = \beta(S_t - S_{t-1}) + (1-\beta)G_{t-1}$$



Triple Exp. Smoothing

This algorithm consider three components to carry out forecasting :

- a Basic Value S_t

- a Trend Value G_t

- a Seasonal Value C_t

$$P_{t,t+\tau} = (S_t + \tau\, G_t)C_{t-s+\tau}$$

τ=Analysis Period

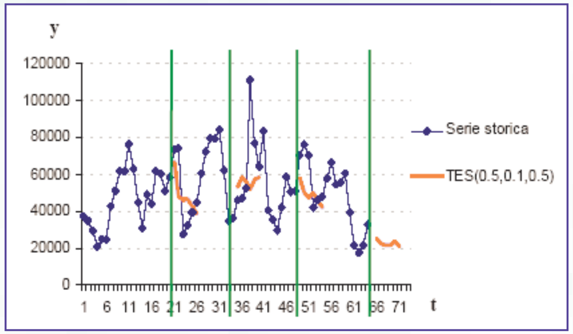
S = seasonal period

The lack of seasonal effect is the most important critical issue of Double Exp. Smoothing

$$S_t = \alpha X_t + (1-\alpha)(S_{t-1} + G_{t-1})$$

$$G_t = \beta(S_t - S_{t-1}) + (1-\beta)G_{t-1}$$

$$C_t = \gamma \frac{X_t}{S_t} + (1-\gamma)C_{t-s}$$

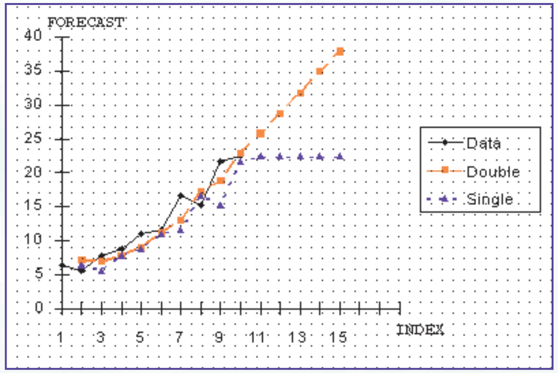


Parameter Optimization

There are several methodologies to calculate the forecast accuracy of the different algorithms. The most common used are:

Total Error Minimization

$$Total\_Error = \sum_{i=1}^{n} Forecast_t - Consumption_t$$

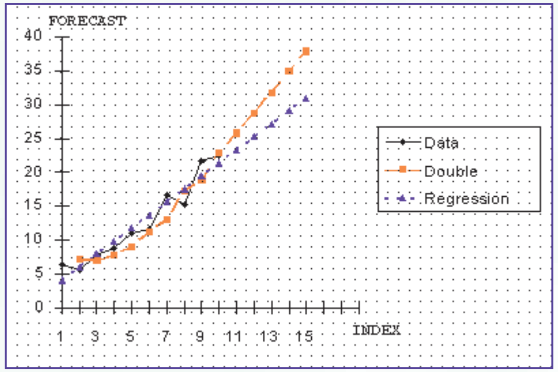


M.A.D. : Mean Absolute Deviation

$$M.A.D. = \frac{1}{n}\sum_{i=1}^{n}\left|Forecast_t - Consumption_t\right|$$

M.S.E. : Mean Squared Error

$$M.S.E. = \frac{1}{n}\sum_{i=1}^{n}\left(Forecast_t - Consumption_t\right)^2$$



The algorithm forecast accuracy is not measured on the minimization of the difference between forecast and actual value but on the robustness.

Algorithm Comparison

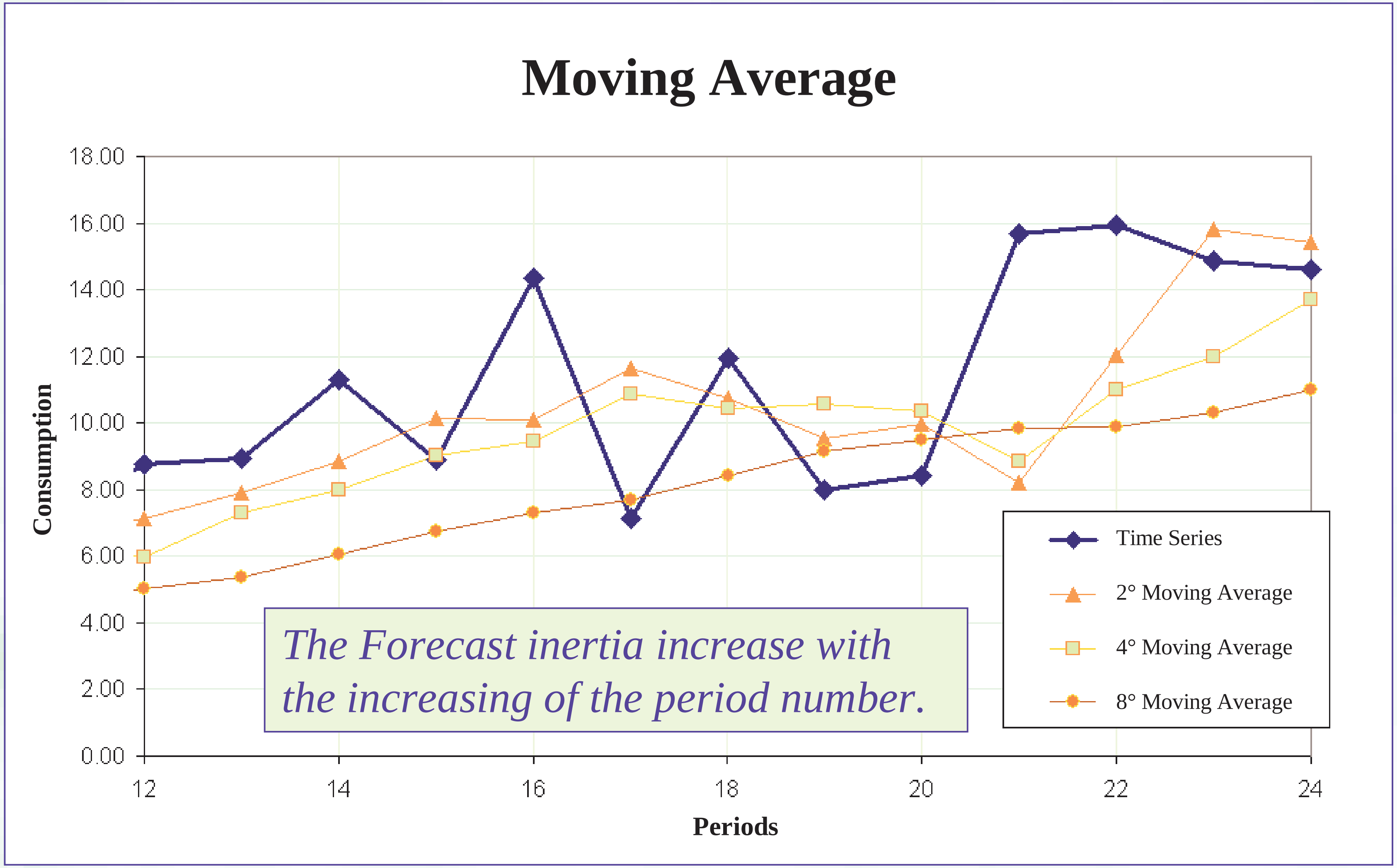
COST/BENEFITS	Influence of Most Recent Data	Less Data Required	Identification of new Trends	Season and Period Identification	Risk to Over Estimate Trend	Risk due to Forecasting Inertia	Critical Influence of Peaks	Complexity of the Model
Moving Average	no ☹	no ☹	no ☹	no ☹	no ☺	yes ☹	no ☺	
Weighted MA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

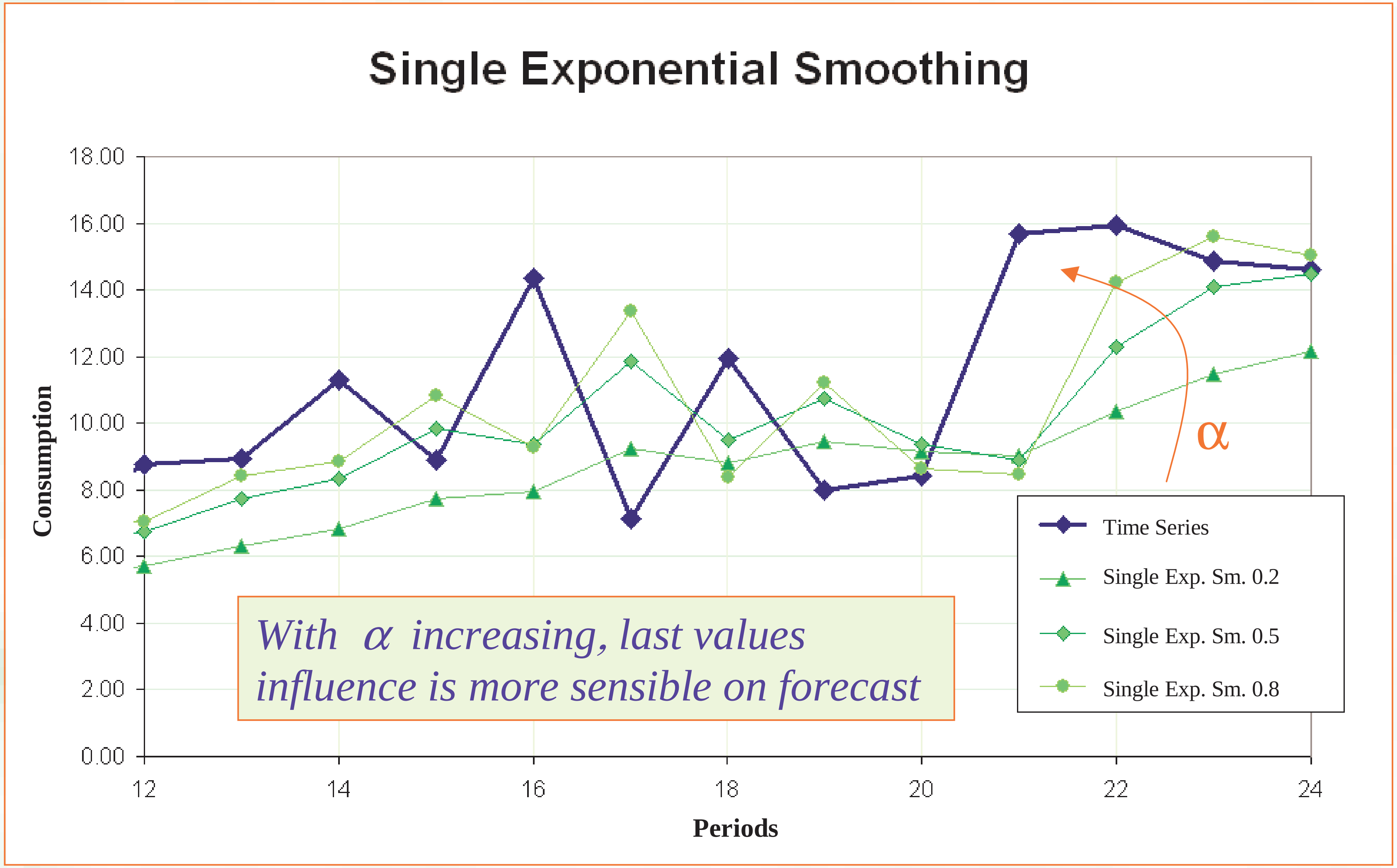
Forecast vs. Time Series

Moving Average Examples



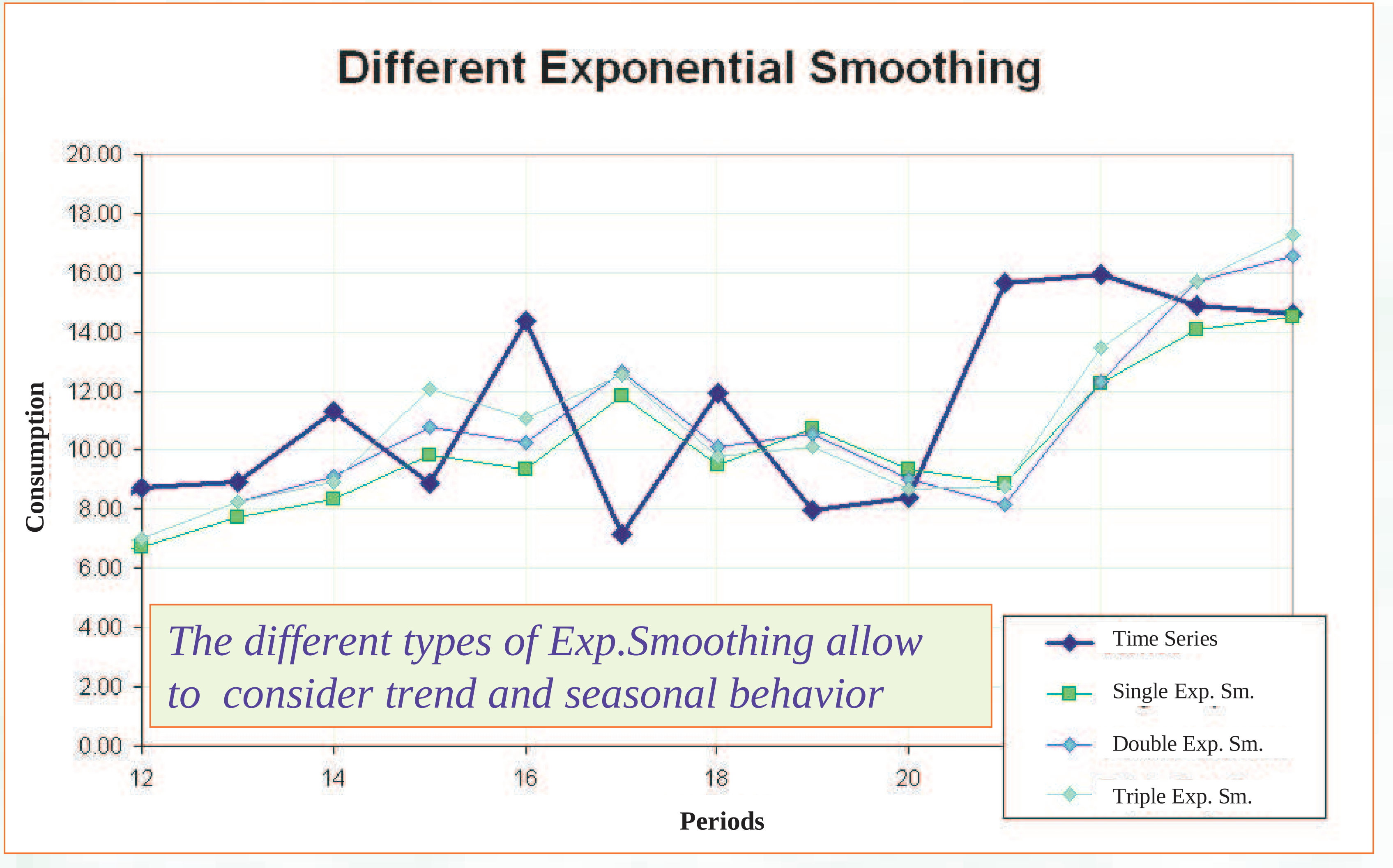
Forecast vs. Time Series

Exp. Smoothing Examples



Forecast vs. Time Series

Single vs. Double vs. Triple



The different types of Exp.Smoothing allow to consider trend and seasonal behavior

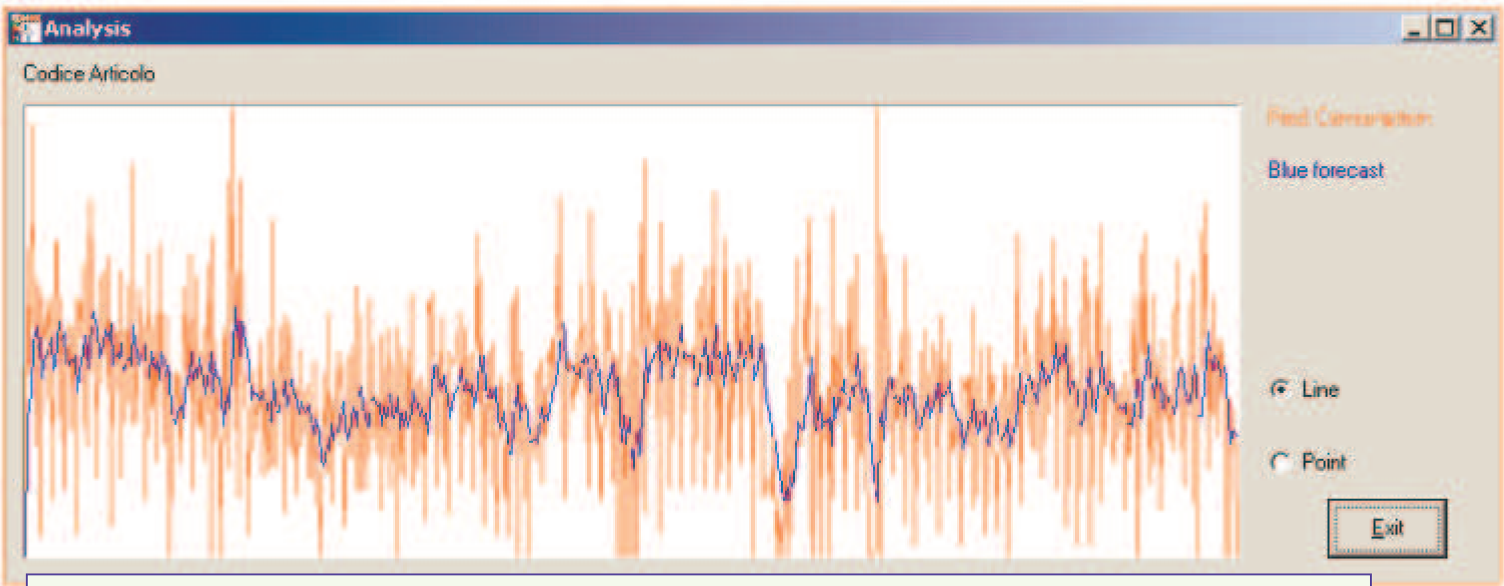
Seasonal Period Analyses

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



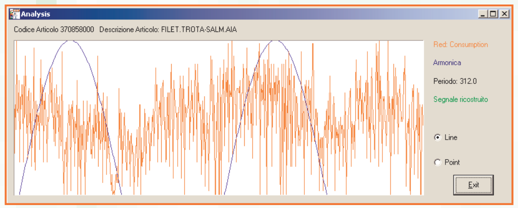
Typically real behaviors with strong stochastic component and high values of Standard Deviation respect the mean value

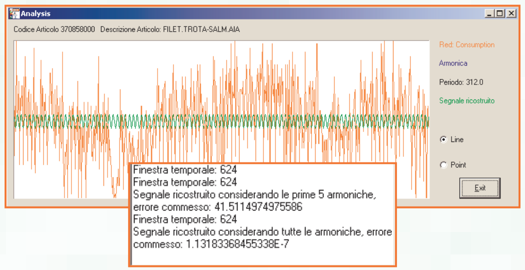
Period Analysis

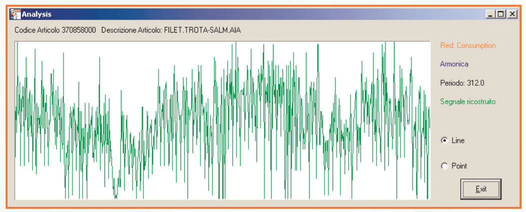
In order to identify a priori possible seasonal behaviors on the demand it is useful to acquire knowledge related to the processes under analysis and to its characteristics.

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.

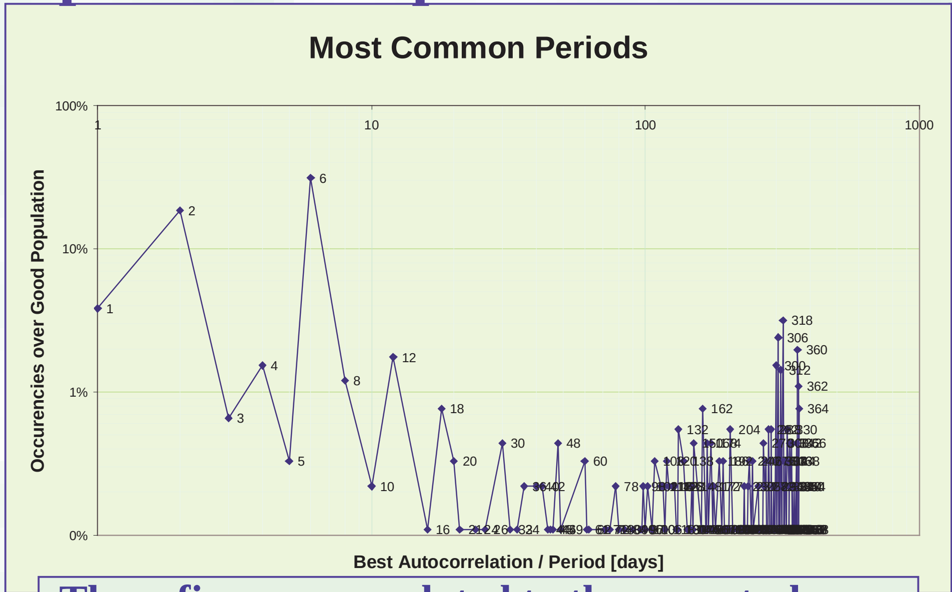




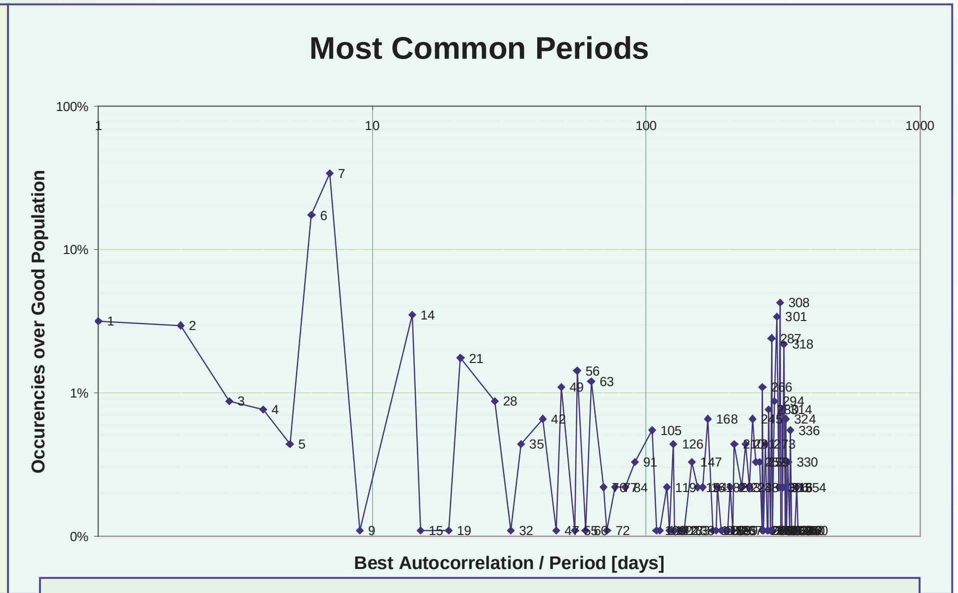


Autocorrelation Analysis

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

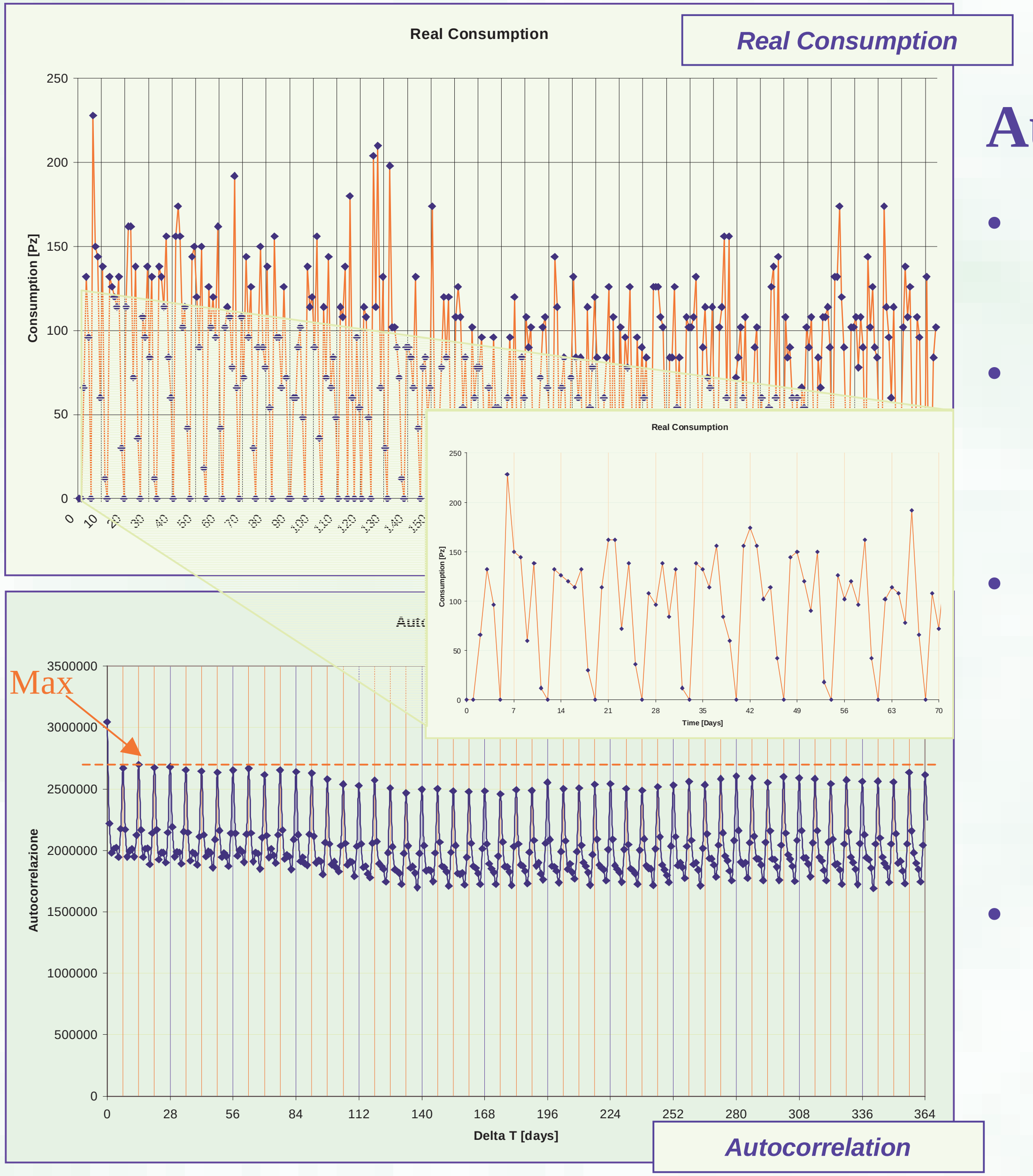


These figures are related to the case study proposed about the demand of frozen goods. These figures consider the week without Sundays (due to the delivery policies in use) it is evident that six days and multiple periods are the most common and significant periodic component.



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

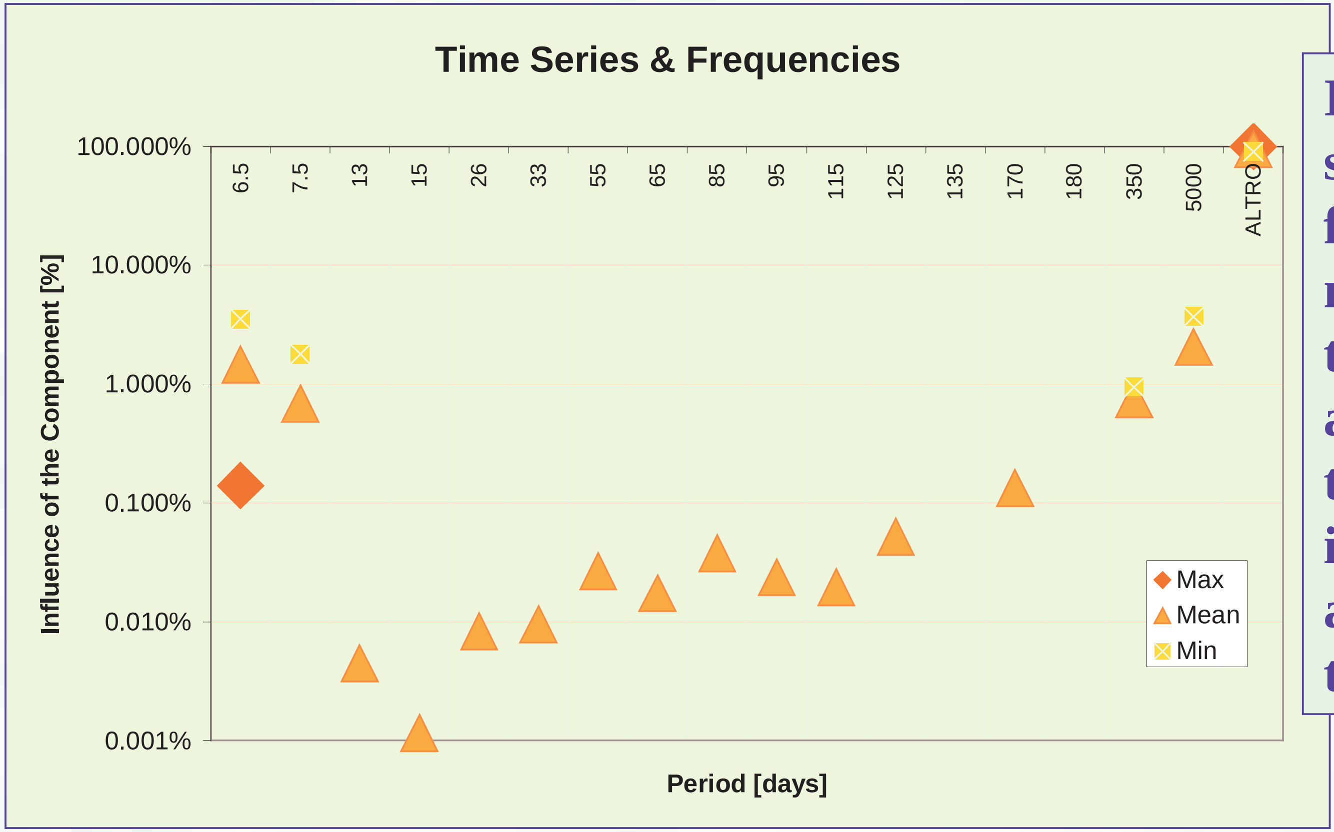
Stochastic and Periodic Components

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.

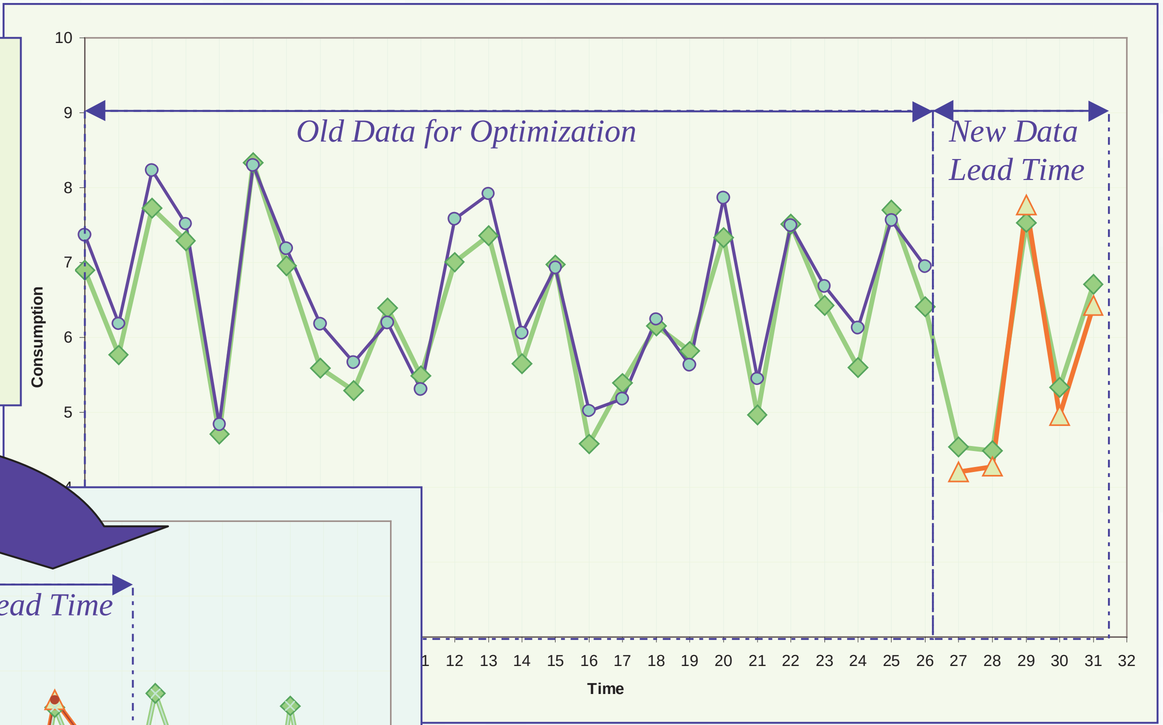
In the case study proposed the M.A.D.calculation was made in two different ways:

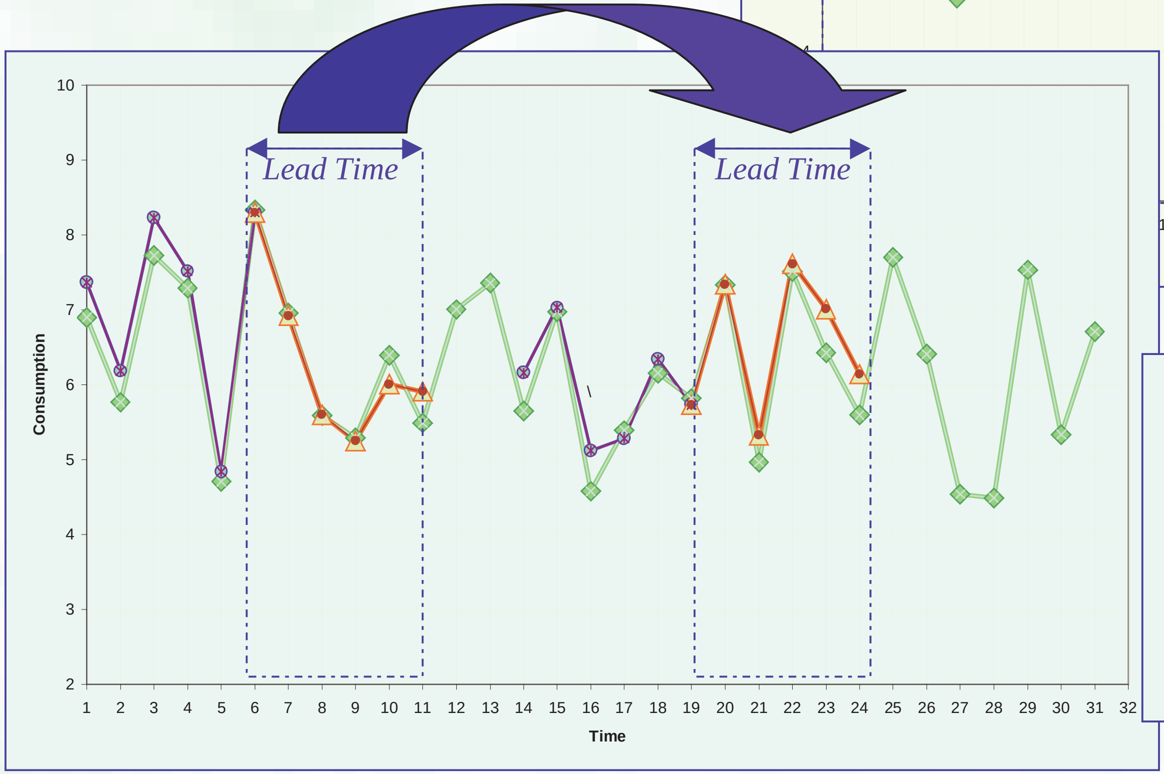
- Lead Time M.A.D.: the forecast is carried out on the Lead Time and the delta among forecast and the time series are calculated.
- Future M.A.D.: the time orison is divided in two part, the first part is the total scenario less then the lead time and the other one is the lead time. On the first part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

Complexity of the Frameworks

It is important to state the complexity of the framework to be analyzed.

To identify the complexity of the problem we can have an hypothesis about the case 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.

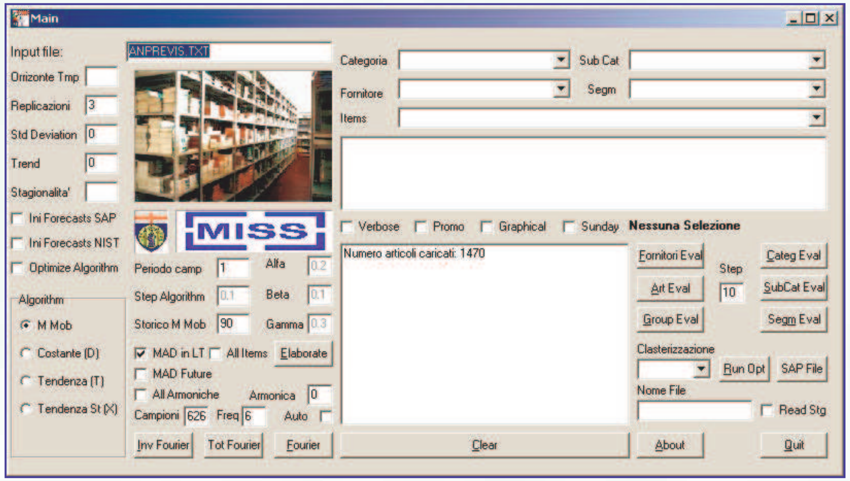
Demand is based on historical data about quantities delivered daily over the supply chain.

Exercise

- ✓ The proposed exercises is related to the Demand estimation of books

- ✓ In this Application case we need to identify how simulation can support forecasting and what results we can obtain

- ✓ Scenario Characteristics:
  - ✓Book Demand
  - ✓1242 Books Types
  - ✓6 Books Categories
  - ✓6 Books Subcategories
  - ✓6 Books Segments
  - ✓6 Books Suppliers

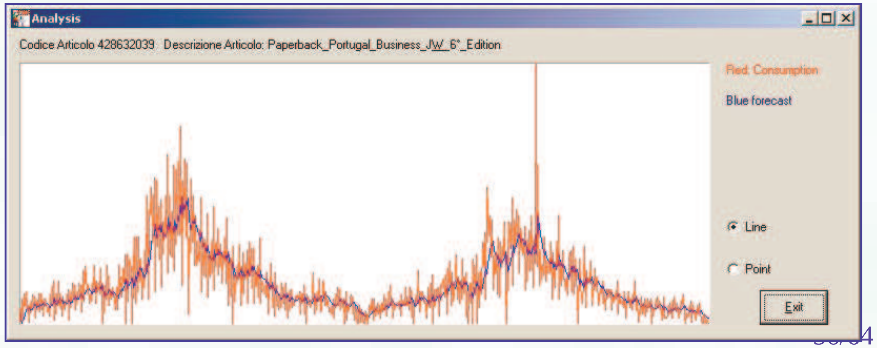


Simulation Settings

- ✓ Simulation in this exercise will be used to:
  - ✓Reconstruct Scenarios from Historical Data based on stochastic components
  - ✓Estimate robustness of algorithms to demand obscillations
- ✓ As Simulationists we need to:
  - ✓Identify the Variability and Trend to be added to historical data
  - ✓Identify the number of Simulation Runs Required to estimate overall performances

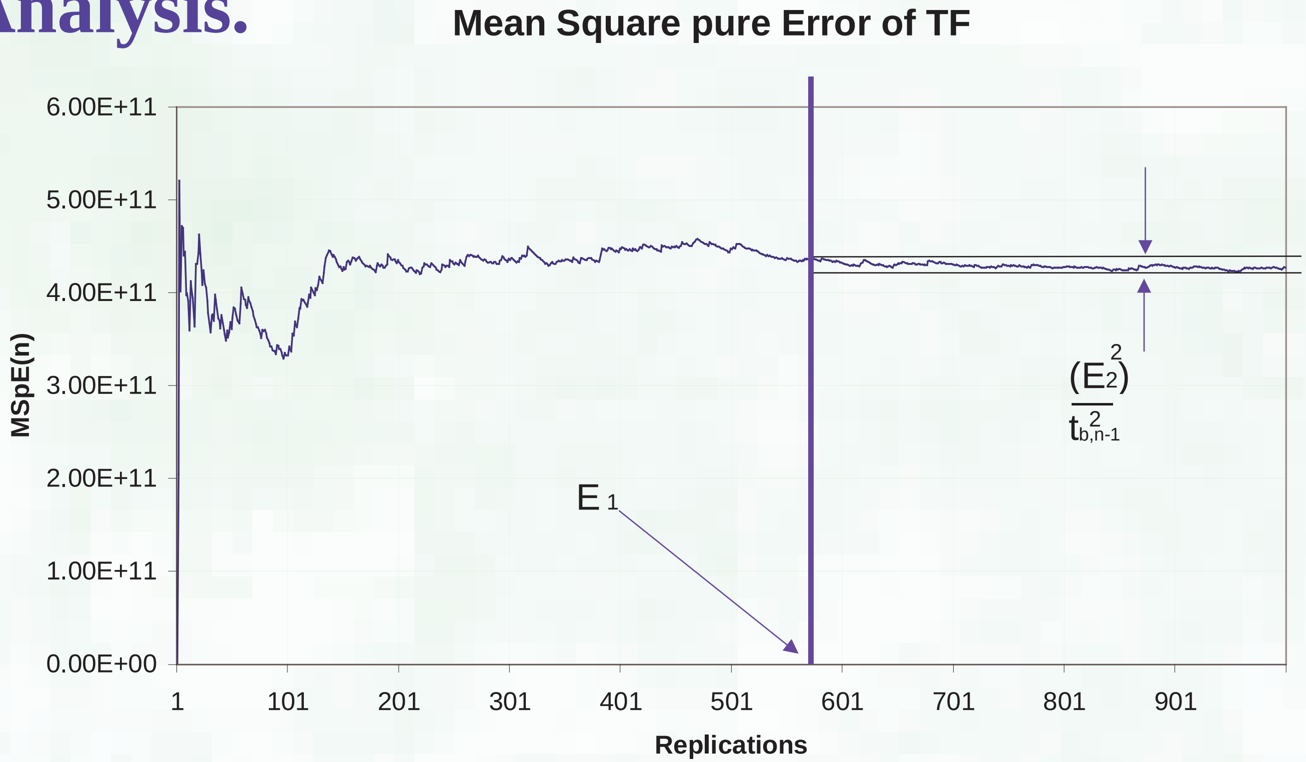
Trend & Noise

- ✓ The analysis of the historical data plus the expert knowledge in this case allows to identify the best setting:
  - ✓ Trend Usually have to be estimated based on last significant period trend analysis (i.e.regression) plus expert expectations
  - ✓ Noise could be based on Standard deviation collected over an analysis window related to a significant period plus expert expectation



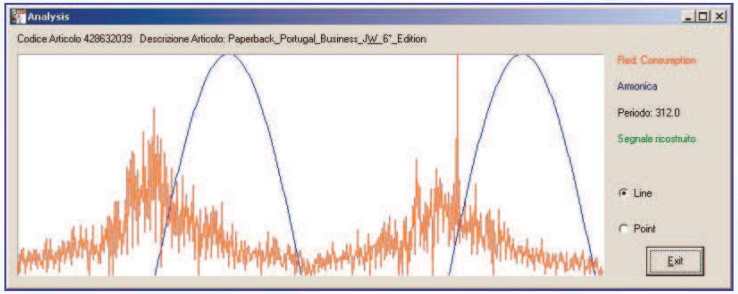
Replications

✓ The simulation requires N replications changing the random seeds in order to provide stable performance; this could be estimated by applying Mean Square pure Error Temporal Evolution Analysis.



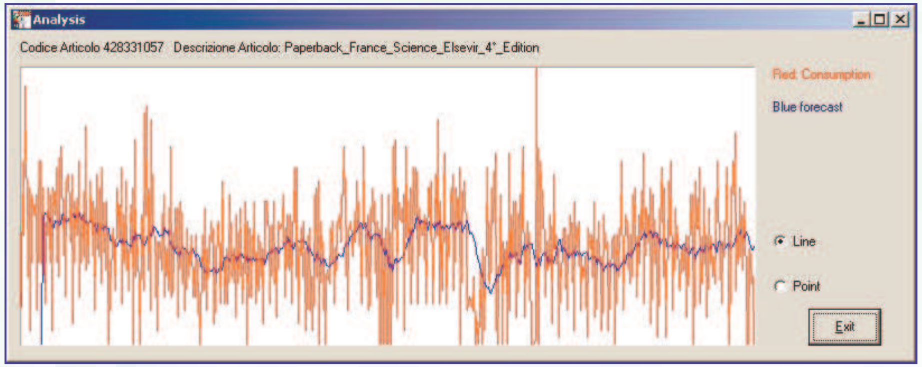
Periodic Component Identification & Evaluation

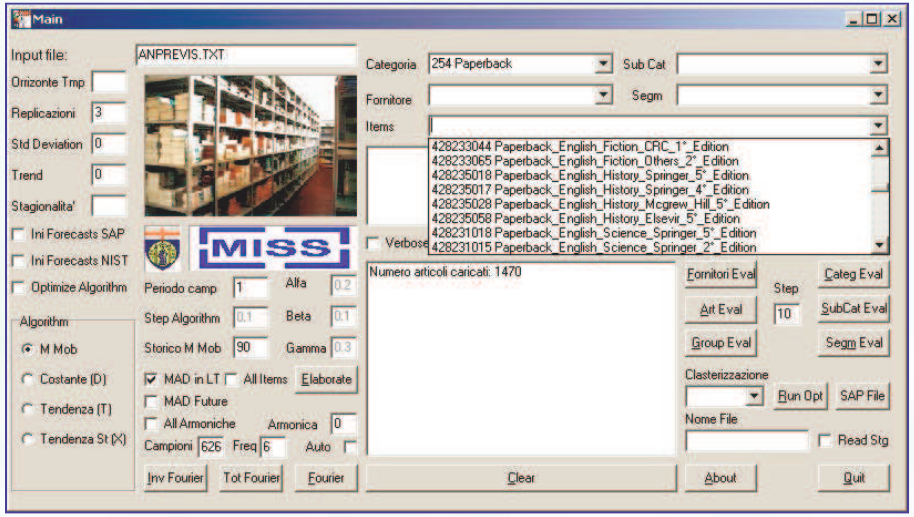
- ✓ In order to complete this part we will:
  - ✓ *Take a Look* on Item Demand over time
  - ✓ Proceed to Autocorrelate each Item Demand
    - ✓ Identification of Most Significant Period
  - ✓ Proceed to Fourier Analysis on Each Item
    - ✓ Identification of Periodic Component Influences



Best Clustering

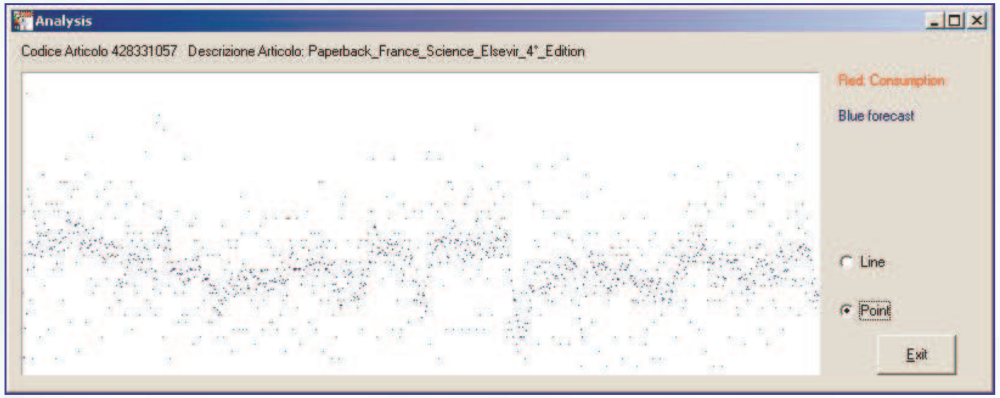
- ✓ Another important result is to use simulation in order to group in the best ways items.
  - ✓ Optimizing each grouping opportunity on best algorithms will provide an estimation of best grouping under different hypotheses

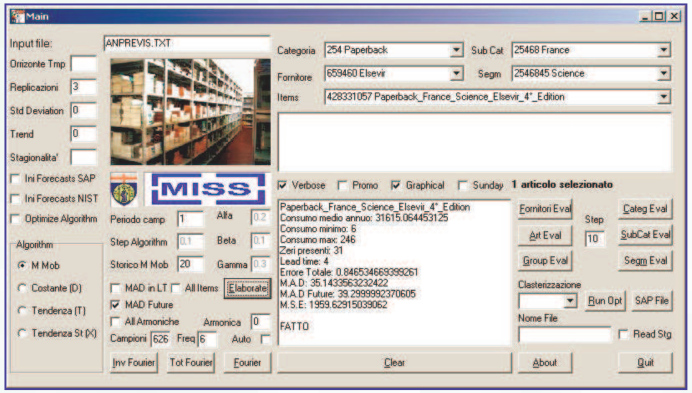




Best Algorithm

- ✓ For each Group it is possible to use simulation to measure overall performances and robustness for:
  - ✓identification of best algorithm
  - ✓best fitting of parameters for best algorithm





Conclusions

- ✓ Simulation can improve performances of forecasting techniques by:
  - ✓ Testing Hypotheses about the real System
  - ✓ Testing a priori their robustness
  - ✓ Identify best Management Policies
  - ✓ Identify best Algorithms and Fitting their Parameters
  - ✓ Evaluating the Operative Margins versus Predictability Levels
- ✓ Simulation can't provide:
  - ✓ Better Estimations on the Models than on real System
  - ✓ Crystal Ball on the Future
  - ✓ Correct Prediction in Random Systems

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References

Liophant Simulation

Liophant Simulation
Headquarters
via Molinero 1
17100 Savona, Italy
Tel +39 019 264 555
Fax +39 019 264 558
URL: www.liophant.org
Email: agostino@itim.unige.it
simone.simeoni@liophant.org

Agostino Bruzzone & Simone Simeoni