The International Maritime Transport and logistics Conference

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The Trends, The Future

8 MarLog 2019

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A DIGITAL TWIN FOR SUPPORTING ENERGY MANAGEMENT IN COMPLEX MARITIME TERMINALS

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Introduction

The **price of electric energy** is actually a key factor for the economic performance of high energy demanding logistics centers.

The complexity of planning operations and the availability of multiple markets allow to create synergic tools for simulation modelling of real scenarios with power consumption management tools.

The mix of energy consumption calculation trough a system dynamics model and the predictive analysis on a short time period for best price buying on the electricity market represents a driving action for logistics planning operation.

This paper shows a **real case implemented into an intermodal logistics center placed in Voltri (Italy), providing an overview of the harbor simulation and energy price forecasting models**, and their role within the interaction among the decision-making personnel, aimed at electric energy purchase cost optimization.

The harbor object of study

The **Voltri Terminal Europe** - V.T.E. is the largest containers terminal of the Port of Genoa (Italy) with an annual capacity of 1,5 million TEU's.

The Voltri Terminal Europe has **3 berths** with 3 vessels that can be served at once, lifting containers from ship bays and unloading on trucks, which transfer it to the container yard. The container yard is equipped with working gantry cranes, which place containers in blocks in a container yard.

After discharging, containers wait until they are carried on a train, external truck or another vessel, or sent to custom inspection on import. The same procedure happens when container arrives with external transport and continue transportation by vessel.

Terminal operating time is 363 days/year, 24 h / 24 h (with the exception of December 25th and May 1st). 4 daily shifts of 6 hours each are provided:

- 1st shift 06:00 - 12:00,
- 2nd shift 12:00 - 18:00,
- 3rd shift 18:00 - 24:00,
- 4th shift 00:00 - 06:00.

Electric power management

Recently, the harbour power source has been switched from an autonomous Diesel generator, to a **connection with the national electric grid**.

This choice has led to certain advantages in terms of local environmental impact; however, **also economic advantages can arise whereas the energy acquired from the national electric grid is managed in an intelligent way**.

Electric energy has a variable cost per kWh in function of time, so **it is possible to design a buying strategy** opportunely *synchronized* with the **required harbour operations**, in order to obtain advantages on the transported materials movement costs.

The management strategy

The **management strategy** employed for the energy costs optimization is based on the interaction between harbour managers and simulation/forecasting tools made available to them. In particular, the actors of the decisional process are:

- The **Harbour Manager**, who is the main responsible for the good outcome of the decisional process. He obtains, as input data, the ships arrival time, by the Estimated Time of Arrival (ETA) document, and the amount of TEUs to be managed, appearing in the Manifest document.
- The **Energy Manager**, who is responsible for the power costs optimization; he receives data from the market, regarding the energy cost for each time slot.
- The **Human Resources (HR) Manager**, who has the data regarding the operative personnel availability, shifts and manpower costs.
- The **Maintenance Manager**, who is in charge for the maintenance exigencies and the availability of the loading-unloading equipment.

The management strategy

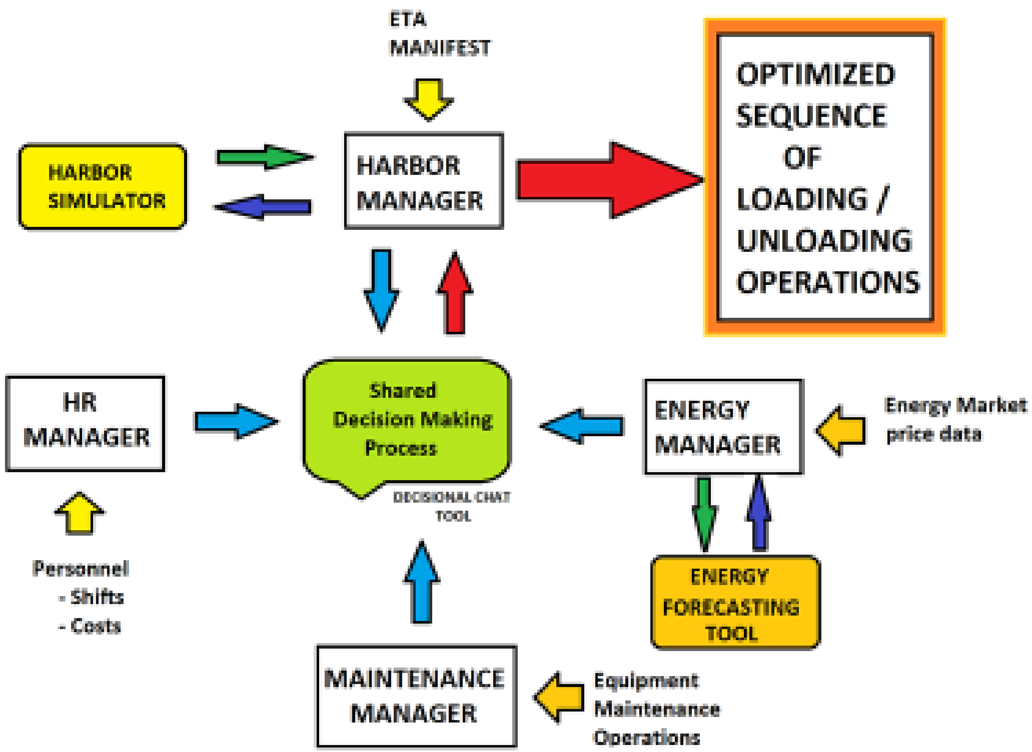
The decisional process is supported by two informatics tools, namely:

- A **harbour simulation model**, which simulates the logistic operation of the harbour, predicting loading and unloading time.
- An **energy market cost forecasting model**, which forecasts the cost of the purchased kWh for each time slot thanks to market prevision models.

These two models are uploaded on a server, so that they are available to the decision managers.

The interaction among the decision managers is supported by a "**decisional chat tool**", which is as well installed on the server, and helps the managers communicate the decisions related to their harbour management activity.

The management strategy



Schematic view of the management interactions

HARBOUR SIMULATION MODEL

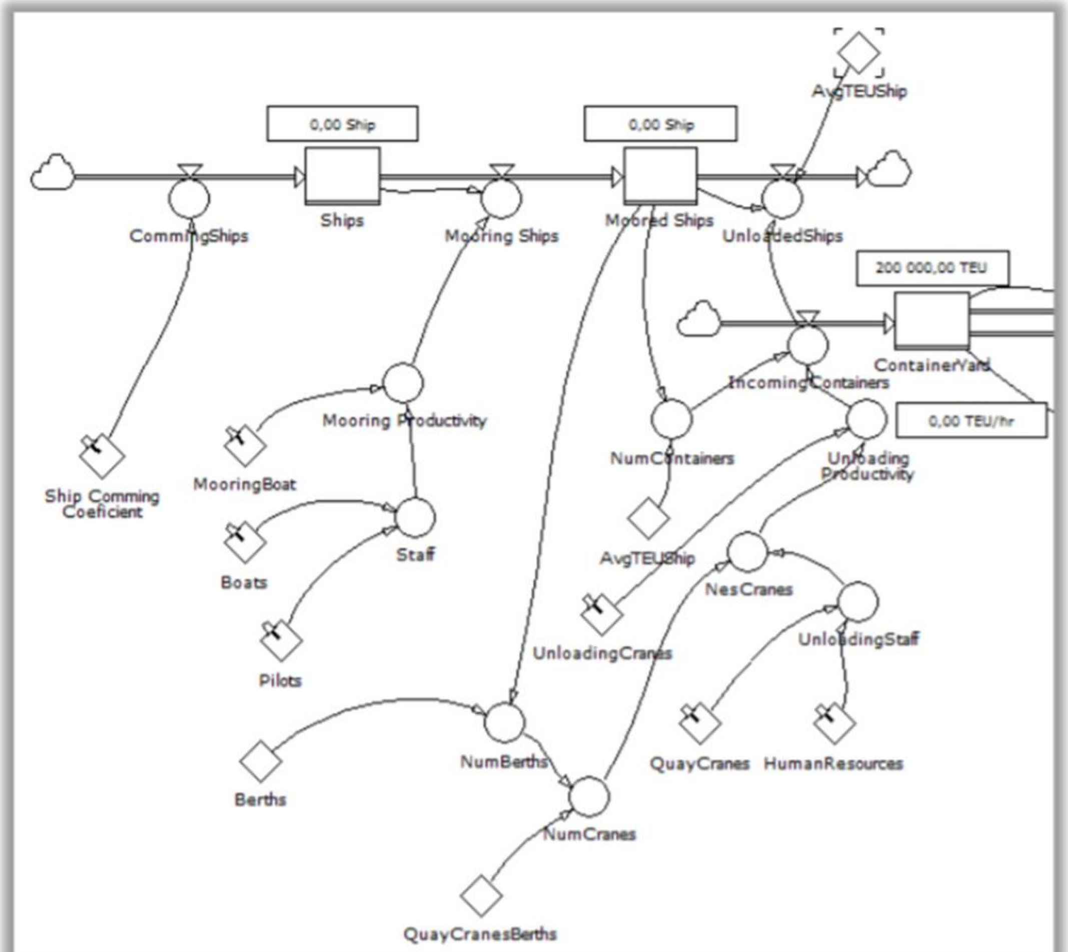
The model simulates the operation of the cranes which make unloading/discharging work and the manpower who works on cranes, influencing productivity of unloading/discharging operations.

The dynamic model is constructed with **Powersim Studio 7 Express**, which allows to build advanced dynamic simulation models of system.

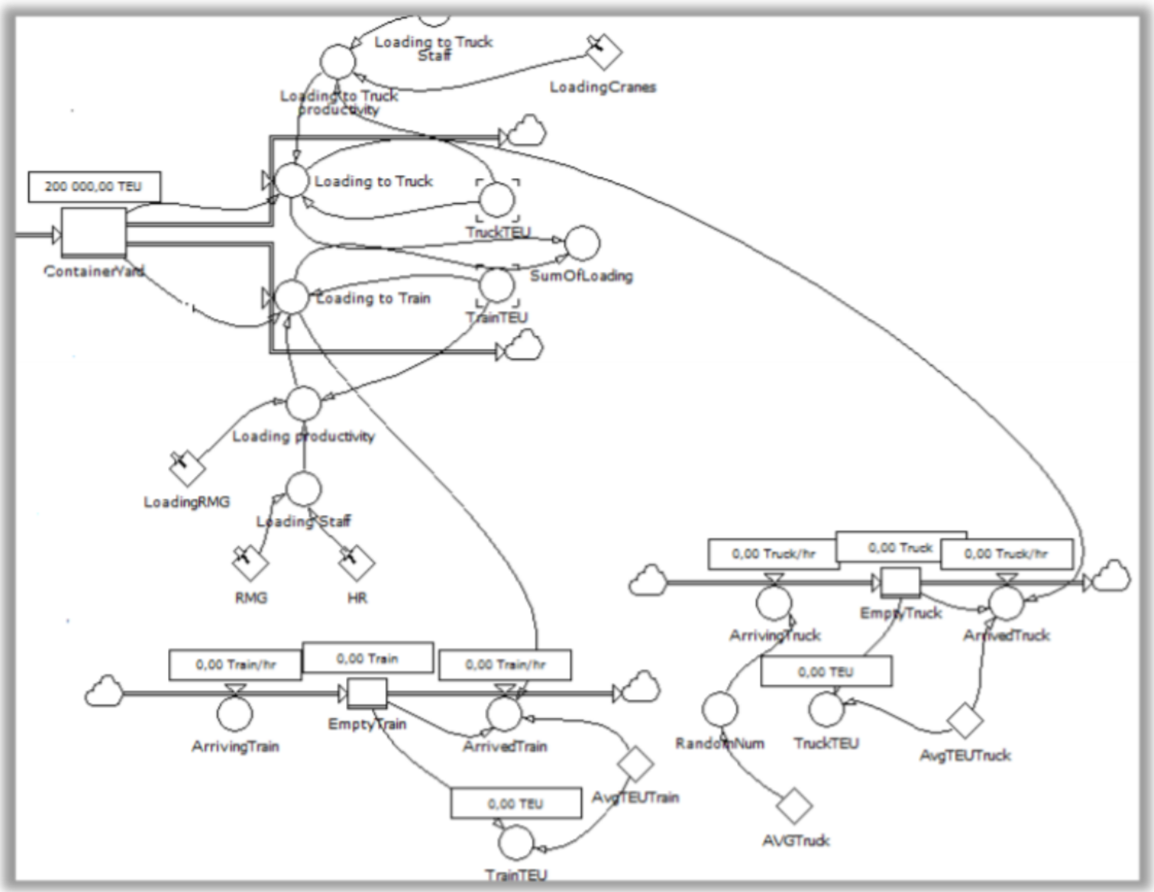
The model consists of flows, levels, rates and constants.

Model of container terminal can be divided on 3 common parts:

- The **first section** is responsible for container ship coming and connected with it mooring and unloading procedures. First part can be divided also for 2 sections, on mooring and unloading sections.
- The **second section** is dedicated to unloading procedures. Common conditions of unloading are described by berths number, which define how many ships can be served in the same time and that number is stored in constant 'Berths'.
- The **third section** is responsible for trains and trucks arrival, departure and loading/unloading.

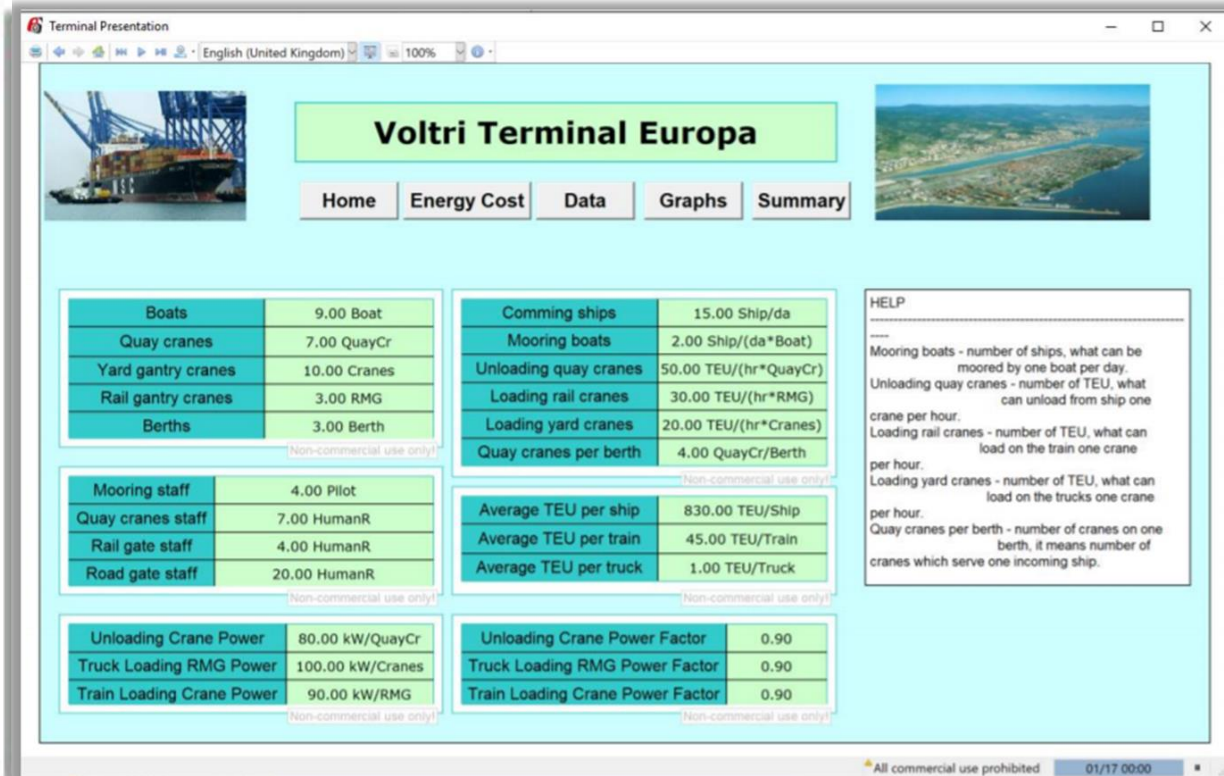


Mooring and unloading of ships



Trains and trucks scheme

Logistic Model



Simulator interface showing the real set up of the terminal.

ENERGY COST FORECASTING TOOL

The embedded tool used behind the model has the aim of **calculating the simulated consumption of electric energy** due to the operation of the logistics center giving back information on costs owned by the logistics center.

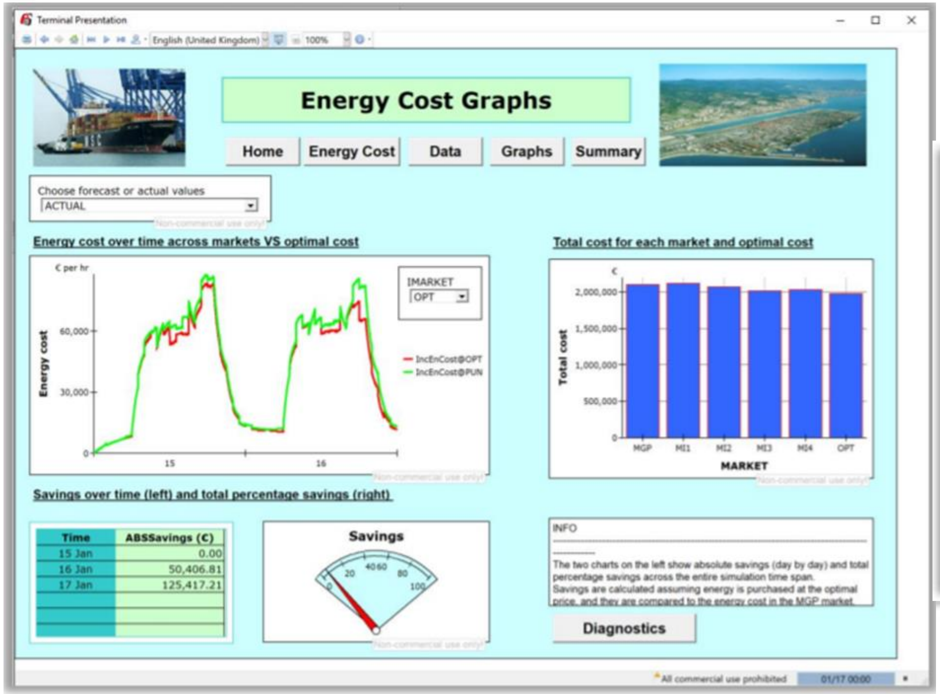
At the same time, the tool is able to **connect to the market exchange** <u>in order to analyze price trends on different markets, to do predictive analysis for the best market</u> in the next 1-2 days and to show comparison between forecasted and real costs due to market choice.

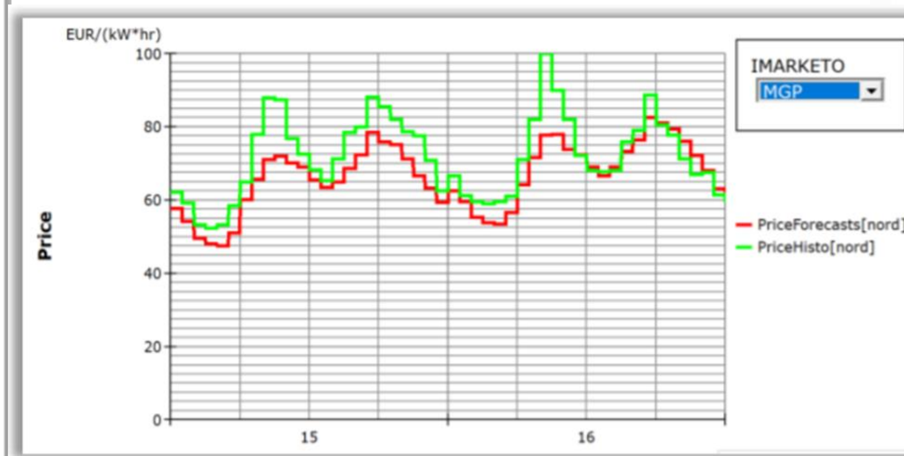
For the predictive model one of the fundamental purpose of the classical analysis of the time series has been taken into account. The components of a historical series Xt are usually the followings: trend (Tt), seasonality (St), cycle (Ct), residual or erratic (Et).

They can be tied up among them in additive way:

$$Xt = Tt + Ct + St + Et$$

Predictive model





Energy cost and power consumption graphs

ENERGY COST FORECASTING TOOL

Once the expected electrical consumption profile is identified, it is necessary to investigate the future price of the electricity in the 5 available markets in order to investigate the best bid strategy for purchasing the required energy. A **forecasting model was then implemented using the Box-Jenkins methodology**.

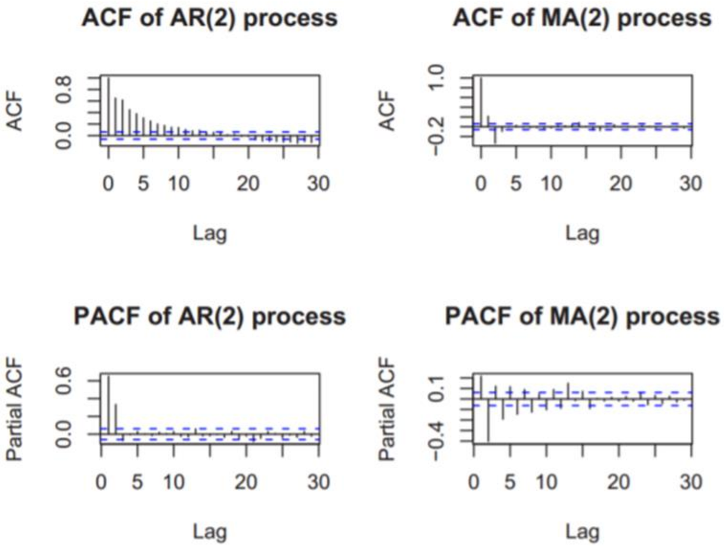
The model individuation was made through the Box Jenkins procedure, which develops in 4 phases:

1) verification of the series stationarity; research of the transformations to make the series stationary
2) identification of the appropriate model and choice of the model orders
3) estimation of the model coefficients
4) verification of the model on the basis of the residuals analysis and of the analysis of the previsions.

For the first point, it is useful the employ of an integrated moving average auto regressive model ARIMA(p,d,q) where the d parameter corresponds to the order of the differentiations to be executed in order to make the model stationary.

Once the verification phase is over, the orders of the model are searched by analyzing the global and partial autocorrelation graphs of the series (differentiated if necessary); SEE NEXT PAGE.

Predictive model



The global autocorrelation function (ACF) is the covariance function normalized on the variance:

$$\rho(k) = \frac{Cov(X_t, X_{t+k})}{\sqrt{Var(X_t)Var(X_{t+k})}}$$

Its value fluctuates between -1 and +1, it is used to see how much the observations in a time series are related to each other.

The partial autocorrelation function (PACF) provides the degree of dependence between one observation and another in which the effects of intermediate values they are removed, so it is purified from the influence of the variables (xt + 1; xt + 2; ... ; xt + k-1) that are in the middle.

Predictive model

In the last stage of the Box-Jenkins method, it is proved that the model obtained can be considered the generator of the analyzed series.

To be able to consider good the model identified, it is required to analyze the parameter estimates and residual estimates, and verify that it is parsimonious, i.e. that the number of parameters used is as small as possible.

First, parameter estimates must be significant different from zero. It must be done (a) a test on the residues that has the task of determining if a seasonal component has remained, in this case the graphs of the ACF functions of the residues show correlations.

To pass the LjungBox test the errors must be truly quite random, as generated by a White Noise trial.

Predictive model

Finally (b) an ex-post forecast is required, i.e. a certain is kept available number of observations for the forecast period, so that the values foreseen by the model they can be directly compared with the observed values. To estimate the model provisional capacity, a Mean Absolute Percent Error (MAPE) indicator can be used:

$$MAPE = \frac{100}{L}\sum_{l=1}^{L}\left|\frac{X_{t+l} - \hat{X}_{t+l}}{X_{t+l}}\right|$$

where:

X_{t+l} is the expected value.

$X\hat{}_{t+l}$ is the corresponding value observed.

L is the number of total observations to be expected.

The verification (a) that historical data are accurate is not important. For the purpose of this work, the interest is focused on the verification of the predictive test (b) as the focus is on the search for the best model to run the forecast in a real application.

MARKET ANALYSIS

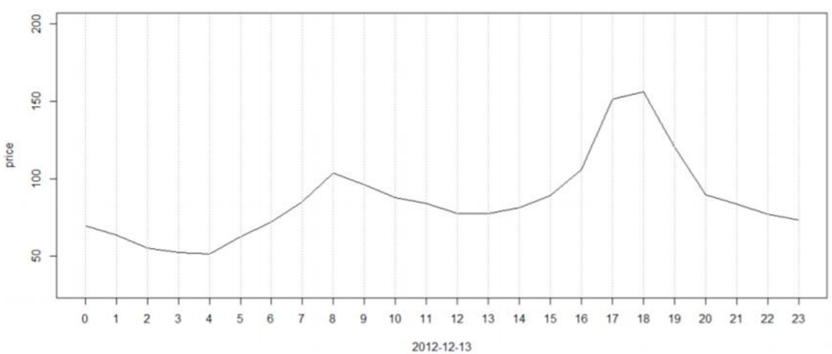
The growing interest in financial markets has led to the development of new techniques, both statistical and economic, able to explain their operation and structure; furthermore, **high frequency data collections** are available (also called intra-day data) that allow the study of new models.

The **very fine data granularity** (one price per hour) shows a <u>high volatility of the price in the long run period</u>. The main causes of these fluctuations during the day are:

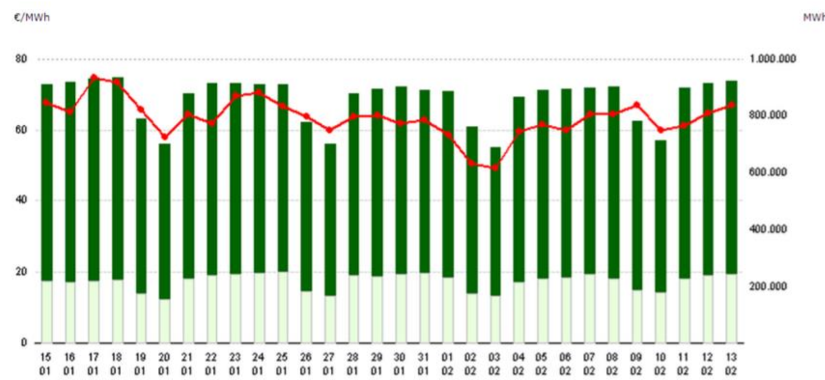
- impossibility of storing large quantities of energy (impossibility of speculation);
- variable demand during the day;
- climate conditions and temperature;
- failures in production plants or lack of water in water basins;
- influence of renewable sources (especially wind);
- festivity;
- economic activities that consume energy;
- other factors including network congestion and market rules.

MARKET ANALYSIS

Figures show a recurring and cyclical pattern that is repeated every seven days; in fact, the average daily price for Sunday is lower than the prices during the week: 20, 27, 3 and 10 correspond to Sundays. Annual seasons, average daily temperatures and hours of light every day introduce an *annual cycle* with regard to domestic consumption. In *summertime* the air conditioners are switched on, so as, in winter, the resistive devices and the illuminations. Furthermore, the renewable energy produced by plants must be taken into account photovoltaic, water and wind power that drastically lower (not predictably) the price.



Prices per hour in a day



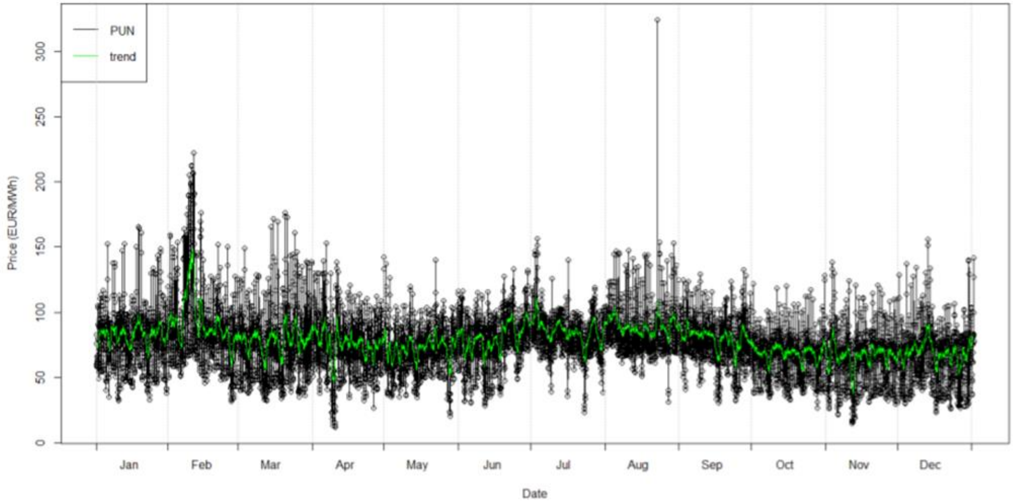
Prices in one month

Real data

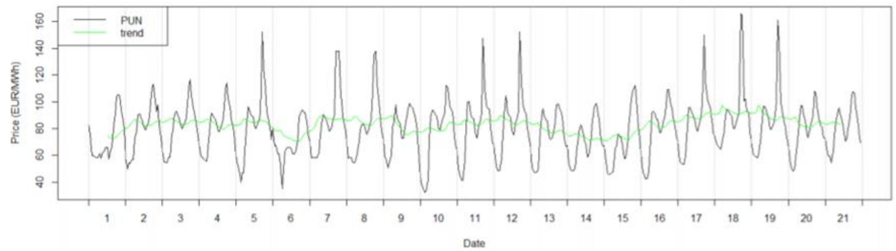
The data analyzed to develop the model come from the Italian electricity market (IPEX or Borsa Elettrica). These consist in five different time series, one for each market managed by Italian Market Manager (GME).

Here is considered only the market series of the day before (MGP).

The MGP PUN price series contains hourly daily prices in euros per megawatt hour (Euro/ MWh) from 1 January to 31 December 2012, therefore 24 X 366 = 8784 observations.



Real price data

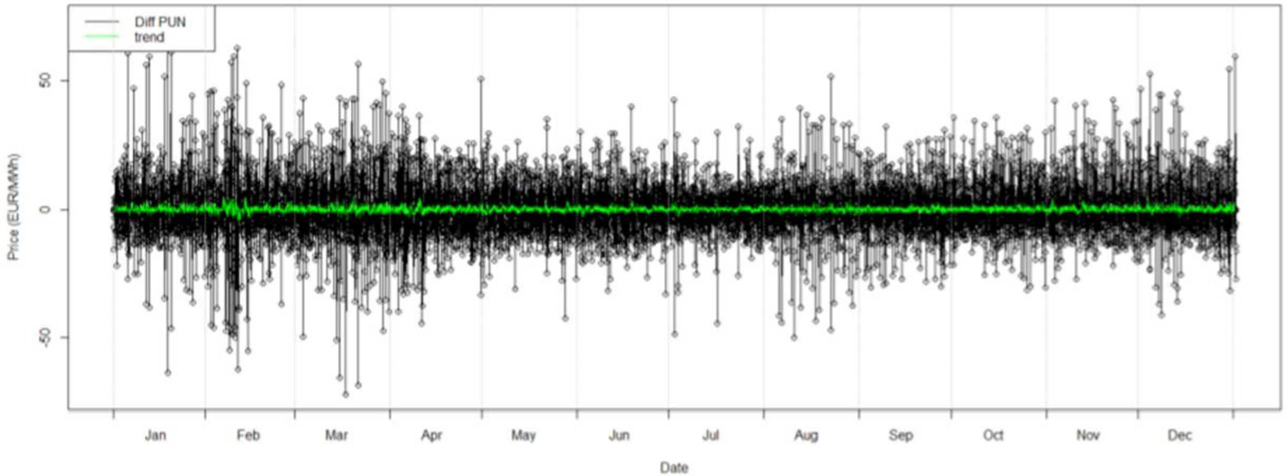


Real price for the first 21 days of the considered month

Real data

Despite the average price (exactly 75.48 Euro/ MWh) is often stationary also considering the monthly subseries, to facilitate the calculation and to bring the average to zero a first-order differentiation was carried out.

The differentiation consists in building a new historical series composed by the differences between two consecutive terms in order to eliminate or reduce the trend.



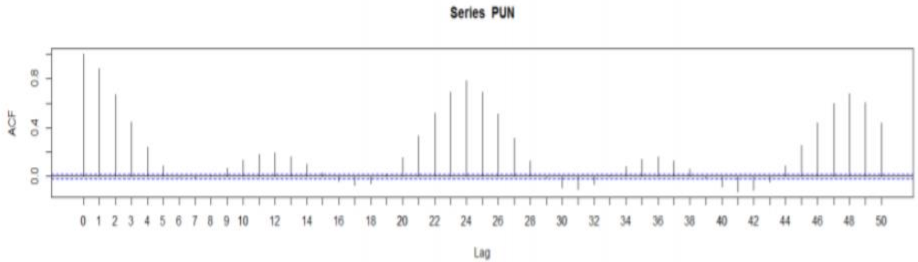
Prices differentiation diagram

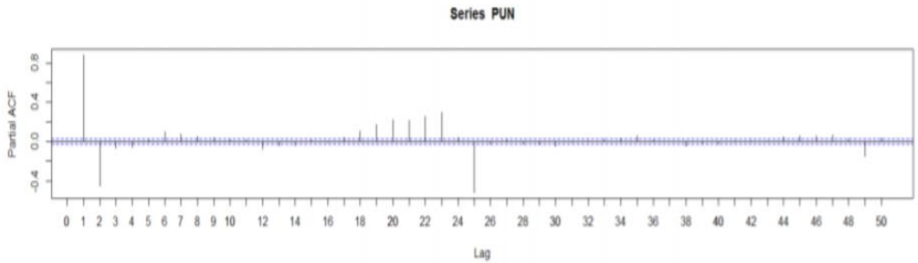
Real data

From the data processed in this way, it is possible to analyze the graphs of the **global and partial autocorrelation functions**.

The PACF function shows two initial peaks in correspondence with the delays 1 and 2; these peaks in the PACF give information on the parameter of the autoregressive part p = 2.

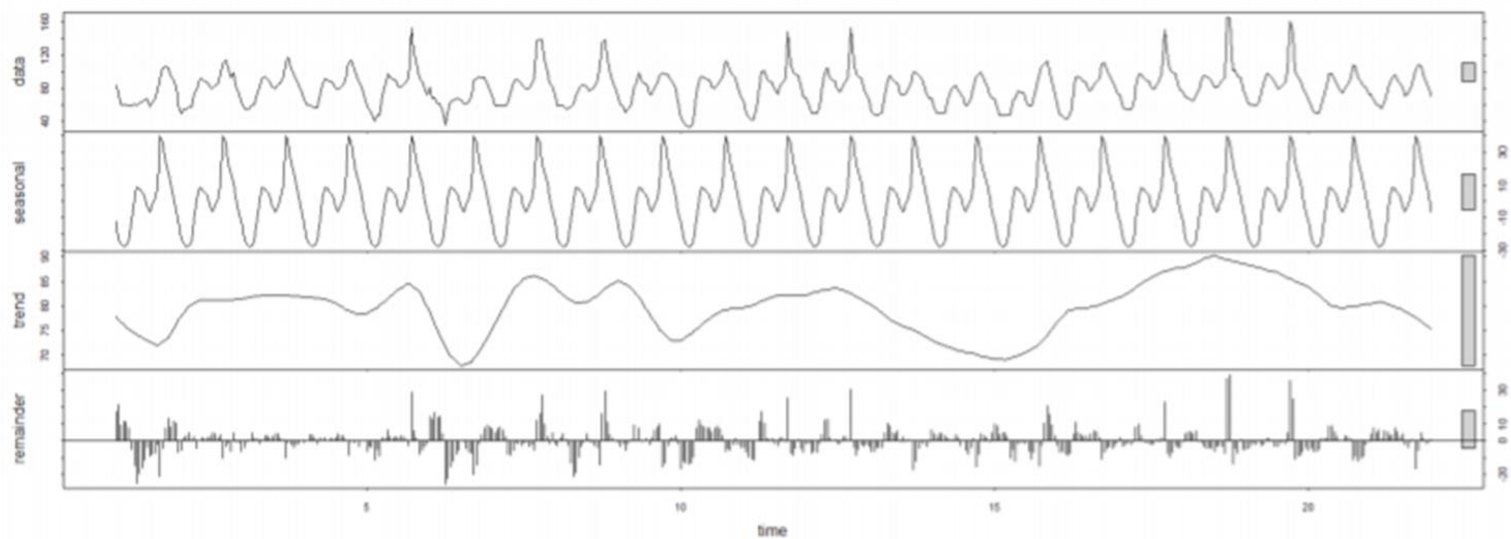
The ACF function shows a decay to zero only after the fifth lag, and subsequently it still fluctuates. This is due to the seasonality and calculation of the ACF, which, being global, takes into account the effects of intermediate lag values. From successive implementations of the model with non-seasonal moving average, the choice of the moving average parameter was q = 0.





Residual analysis

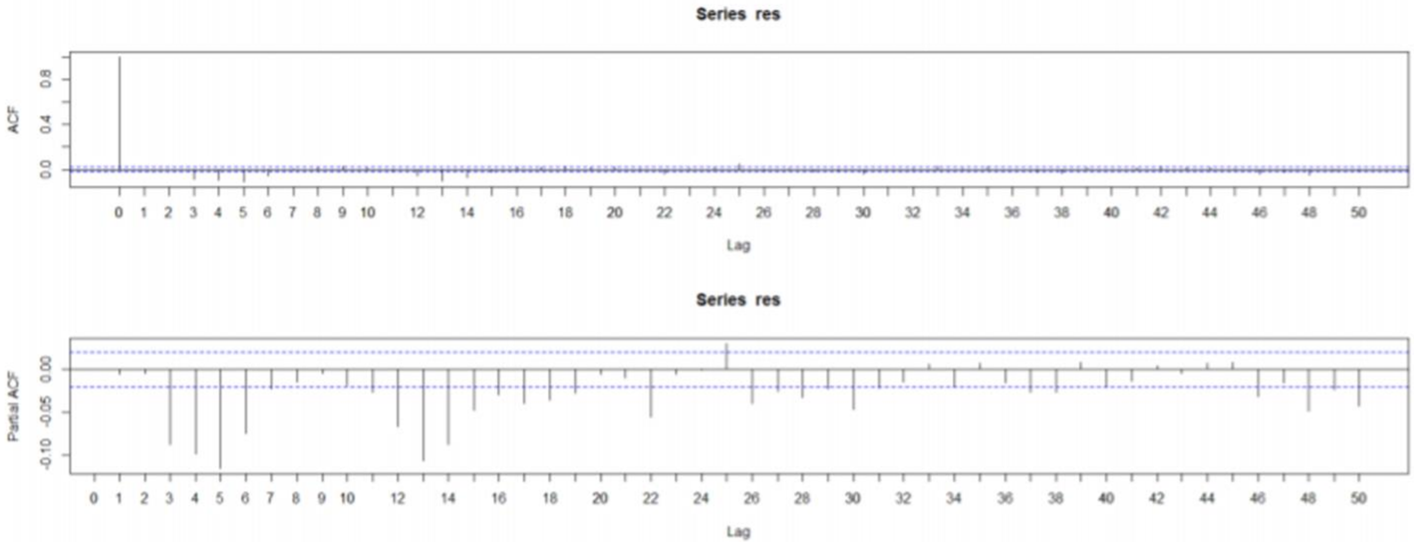
The purpose of this analysis is to check if the error is a realization of a process white noise with Gaussian components. The PUN time series has been decomposed using the SARIMA model (2,1,0) (1,1,1) over the period of 24 h: given the amount of data, Figure shows the decomposition of only the first 504 prices of the year.



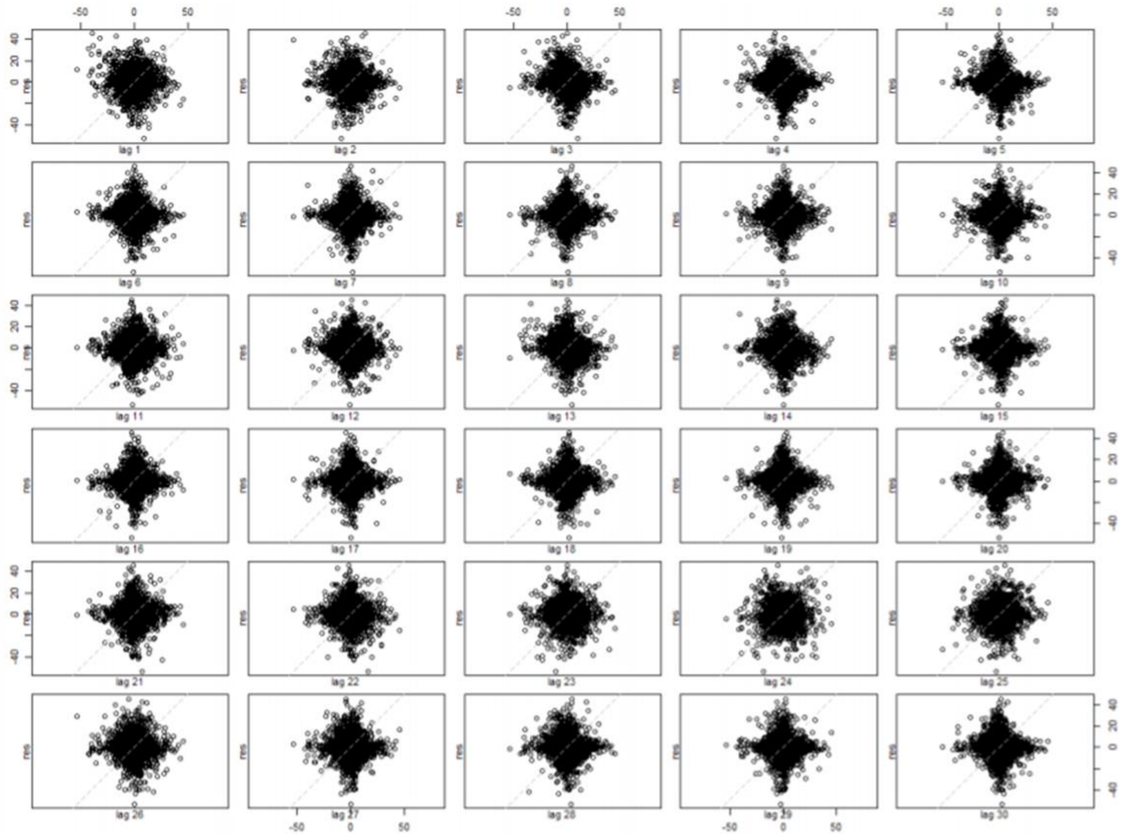
Decomposition of hourly prices in first 241 days

Residual analysis

By plotting the global and partial autocorrelation diagram of the residuals, we note that the periodic components of the series could not be completely eliminated. The global autocorrelation shows that there were periodicities at delays 3, 4, 5, 6, 12 and 13, which however appear to be very close to the confidence interval (marked with the dashed blue line). In the partial autocorrelation chart, in Figure 15, are visible similar periodicities that always result in an interval between - 0.1 and 0.1.



Residual analysis



Self-dispersion diagrams for hourly prices

From the self-dispersion graphs can be observed the dispersion between the original series and the same series retarded of a lag, in Figure we see the auto-dispersion for the lags from 1 to 30.

There are no particular lags for which the series of errors is correlated or anti-correlated, so there seems to be no correlation between the residuals.

Forecasting assessment

To evaluate the predictive performance, the percentage Mean Daily Error (MDE) was used, which is more robust than the MAPE since it considers the error with respect to the average daily price and not compared to the hourly price (which can vary up to100 Euro/ MWh within the same day). The MDE avoids unfavorable effects when prices are close to zero and is so defined:

$$MDE = \frac{100}{24}\sum_{l=1}^{24}\left|\frac{X_{t+l}-\hat{X}_{t+l}}{\overline{X}_t}\right|$$

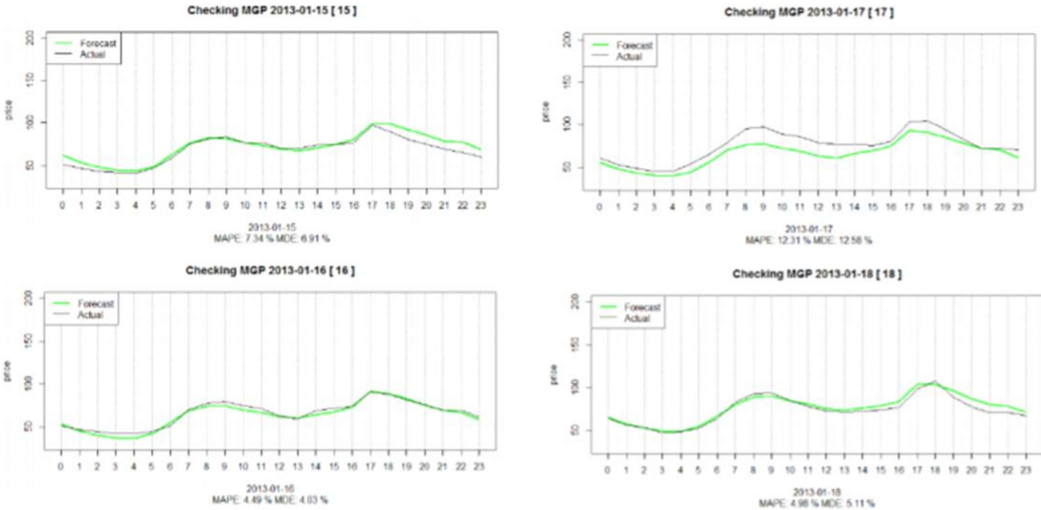
MDE of the energy price for one month period

Day	MDE PUN
15/01/2013	6,91
16/01/2013	4,03
17/01/2013	12,58
18/01/2013	5,11
19/01/2013	12,12
20/01/2013	14,56
21/01/2013	7,44
22/01/2013	5,31
23/01/2013	12,85
24/01/2013	4,12
25/01/2013	5,87
26/01/2013	9,14
27/01/2013	19,53
28/01/2013	8,79
29/01/2013	6,01
30/01/2013	7,51
31/01/2013	6,16

Day	MDE PUN
01/02/2013	7,37
02/02/2013	8,44
03/02/2013	14,19
04/02/2013	8,19
05/02/2013	5,97
06/02/2013	5,51
07/02/2013	13,21
08/02/2013	4,43
09/02/2013	6,94
10/02/2013	12,67
11/02/2013	7,83
12/02/2013	14,66
13/02/2013	4,23
14/02/2013	7,25
15/02/2013	5,60

Forecasting assessment

Figure shows the trend of the comparison forecast to the actual observations for the days 15, 16, 17 and 18 January; these days have different MDE values from 4 to 12 and therefore represent the behavior of the overall prediction.



Prevision in comparison with real data for four days

In general, the results are good, and the forecasts particularly different from reality can be explained by phenomena unpredictable with the only market data.
Electricity prices depend on many factors such as, atmospheric data; gas prices of the previous days; environmental temperature; hour of the day; day of the week; demand of the day before; season; festivity; level of water basins.
The forecasting model has been successfully employed in previous papers to forecast the price of electric kWh in steelworks.

CONCLUSIONS

This work has addressed the problem <u>*of energy supply during the planning phase of an intermodal logistics center*</u>. The problem is typical of each highly energy demanding site or plant in which the price of energy greatly influences the economics of the owner and the price of the service.

The idea of a software tool inside a simulator solution is very innovative and so far it was not yet has been addressed; the developed platform was initially born as a concept. In this way, looking for a technological solution to the problem, different realities were analyzed: the Italian electric market and the logistics intermodal area.

The study of statistical models was of fundamental importance for the analysis of market data and for forecasting future prices.

Starting from these bases, **a platform for decision support has been developed in order to guide who manages logistics planning to select the best plan in terms of bill expenditure**.

The platform has been designed and implemented concretely using a powerful simulation modelling software known as PowerSim in order to be functional and extendable to further establishments.