A DIGITAL TWIN FOR SUPPORTING ENERGY MANAGEMENT IN COMPLEX MARITIME TERMINALS

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ABSTRACT

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 managed as a national power exchange allow to create synergic tools for simulation modelling of real scenarios with power consumption inner tool used for electric consumption management. 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.

Keywords: Systems dynamics, container terminal modelling, Energy price, predictive algorithm, Energy Market.

1 INTRODUCTION

The Voltri Terminal Europe - V.T.E. is the largest containers terminal [1,2] of the Port of Genoa (Italy) with an annual capacity of 1,5 million TEU's. VTE has extensive shipping connections [3] with all world regions (Far East, Middle East, North, Central/South America) and dedicated direct road and rail connections provide the access to an excellent inland transportation network. VTE offers also another type of delivery, by trucks [4 - 6]. Main south European markets are linked within a maximum time of 2 days.

The Voltri Terminal Europe has 3 berths with 3 vessels that can be served at once. So, when a container vessel arrives, the pilot boat pulls the vessel into the berth where several quay cranes discharge it. They pick up containers from ship bays and put it down to loading/unloading trucks, which transfer it to the container yard. The container yard is equipped with working gantry cranes, which place containers into blocks in a container yard by picking them up from loading/unloading trucks [5]. If it is necessary to re-arranging containers in container yard to minimize delivering operations, marshalling trucks are used. After discharging, containers wait until they are carried on a train, external truck or another vessel, or go to custom inspection on import. The same procedure happens vice versa, 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). There is 4 daily shifts of 6 hours each:

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

2 ELECTRIC POWER MANAGEMENT STRATEGY

Recently, the harbour power source has been switched from an autonomous Diesel generator, providing power to all the installed electric equipment, to a connection with the national 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.

From this viewpoint, it can be stated that electric energy has a variable cost per kWh in function of time, so it is possible to design a buying strategy [7-9], opportunely synchronized with the required harbour operations, in order to obtain advantages on the transported materials movement costs.

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:

- <u>The Harbour Manager</u>, 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.
- <u>The Energy Manager</u>, who is responsible for the power costs optimization; he receives data from the market, regarding the energy cost for each time slot.
- <u>The Human Resources (HR) Manager</u>, who has the data regarding the operative personnel availability, shifts and manpower costs.
- <u>The Maintenance Manager</u>, who is in charge for the maintenance exigencies and the availability of the loading-unloading equipment.

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

- A <u>harbour simulation model</u> (described in Section 3) [10,11], which simulates the logistic operation of the harbour, predicting loading and unloading time.
- An <u>energy market cost forecasting model</u> (described in Section 4) [12,13], 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 decisional process can be schematized as in Figure 1.

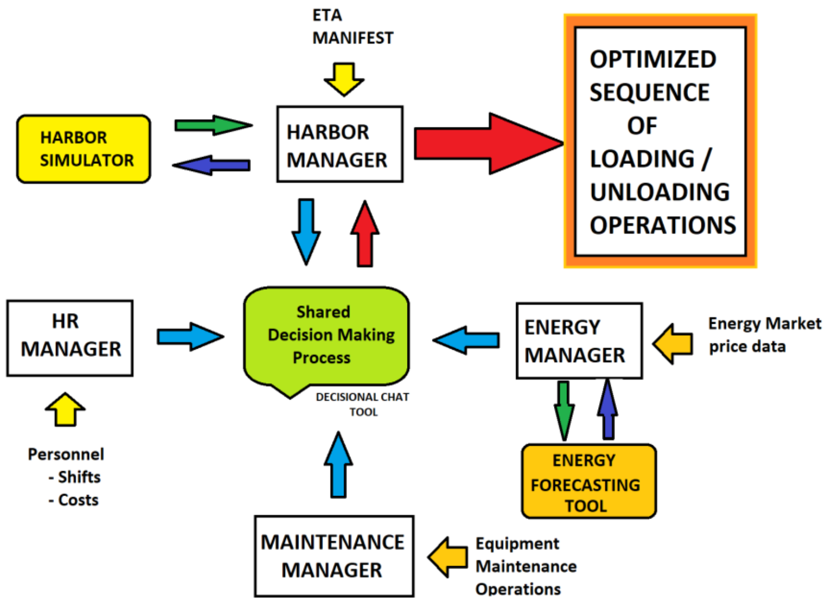

Figure 1: Scheme of the decisional process, supported by harbor simulation model and energy cost forecasting tool.

3 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. Model consists of flows, levels, rates and constants.

Model of container terminal can be divided on 3 common parts. One part 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. In the first part of model there are 3 levels: ‘Ships’, ‘Moored Ships’ and ‘ContainerYard’. These levels types are reservoir (cannot be depleted below zero). In ‘Ship’ level is accumulated the number of incoming ships. The incoming ships are moored and the number of moored ships is accumulated in the ‘Moored Ships’ level. ‘ContainerYard’ level count the number of incoming and outgoing containers. Constant ‘Ship Coming Coefficient’ content the number of incoming ship per day. It’s connected with the auxiliary ‘Coming Ships’. Since it is not possible to know beforehand the exact number of ships coming in a particular day, in the rate ‘Coming Ships’ the function EXPRND ('Ship Coming Coefficient') is used. This function generates random numbers that are exponentially distributed with a mean value of constant ‘Ship Coming Coefficient’. So in a simulation period every day different number of ships will come. Constants ‘Boats’ and ‘Pilots’ content number of boats and pilots. Pilots function is to pull ship into the berth by boat. In auxiliary ‘Staff’ is used a formula, which defines the availability of mooring staff considering that for one boat is necessary two pilots. Constant ‘MooringBoat’ is the number of ships that can be served by the mooring staff per day. So, general mooring productivity is in auxiliary ‘Mooring Productivity’, that is obtained multiplying the available number of mooring staff by the mooring staff productivity. Auxiliary ‘Mooring Productivity’ is connected with rate ‘Mooring Ships’, where coming ships from level ‘Ships’ pass in the status of ‘Moored Ships’ with speed defined in Auxiliary ‘Mooring Productivity’.

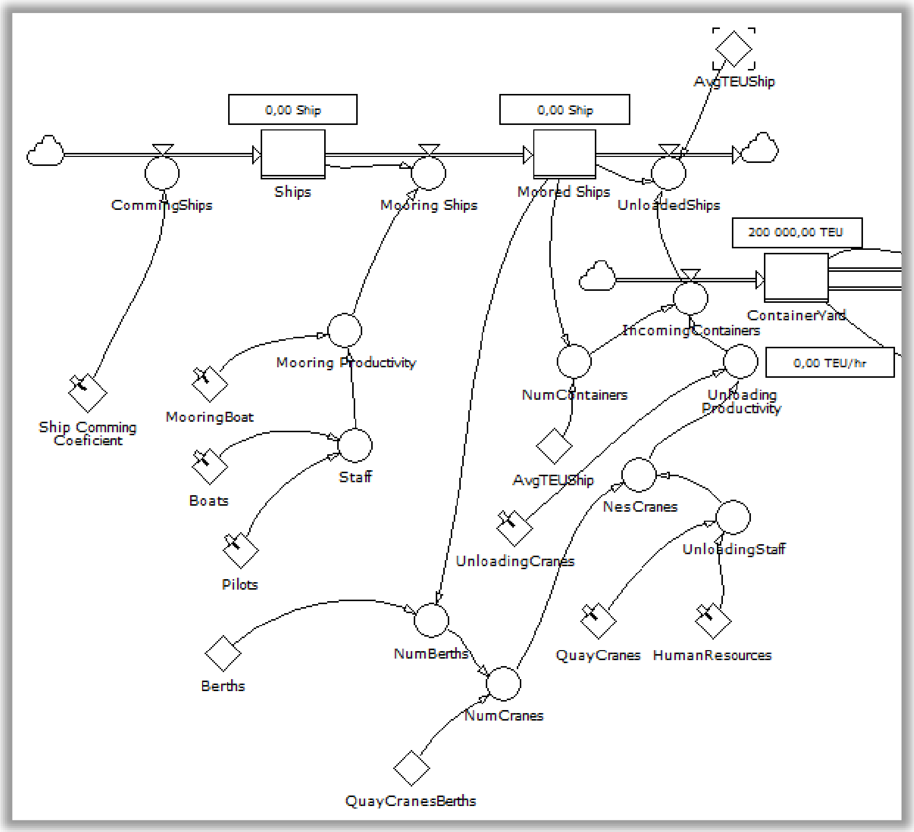

Figure 2: Mooring and Unloading parts of the model

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 other important condition is the available number of quay (total and per berth): those numbers are stored in constants ‘Quay Cranes’ and ‘QuayCranesBerths’. Quay cranes can’t work by themselves, so it is necessary have human resources who control the quay cranes. That number is stored in constant ‘Human Resources’. Three factors: number of quay cranes, human resources and necessary number of human resource to one quay cranes define theunloading staff (auxiliary ‘UnloadingStaff’). The next step is to define in constant ‘UnloadingCranes’ the quay crane productivity, in other words, how many containers can unload one quay crane in the time unit. So, the general possible unloading productivity is in auxiliary ‘Unloading Productivity’ and it is equal with available unloading staff multiplied with one crane unloading productivity. Quay cranes unload containers from ship, so, it is necessary to know how much containers are in ship. It’s average value stored in constant ‘AvgTEUShips’. Final coming containers are calculated in auxiliary ‘NumContainers’, as the moored ships multiplied by the average number TEU per ship.

On Figure 7 the second and the third parts of divided model are shown, and they are responsible for trains and trucks coming and loading.

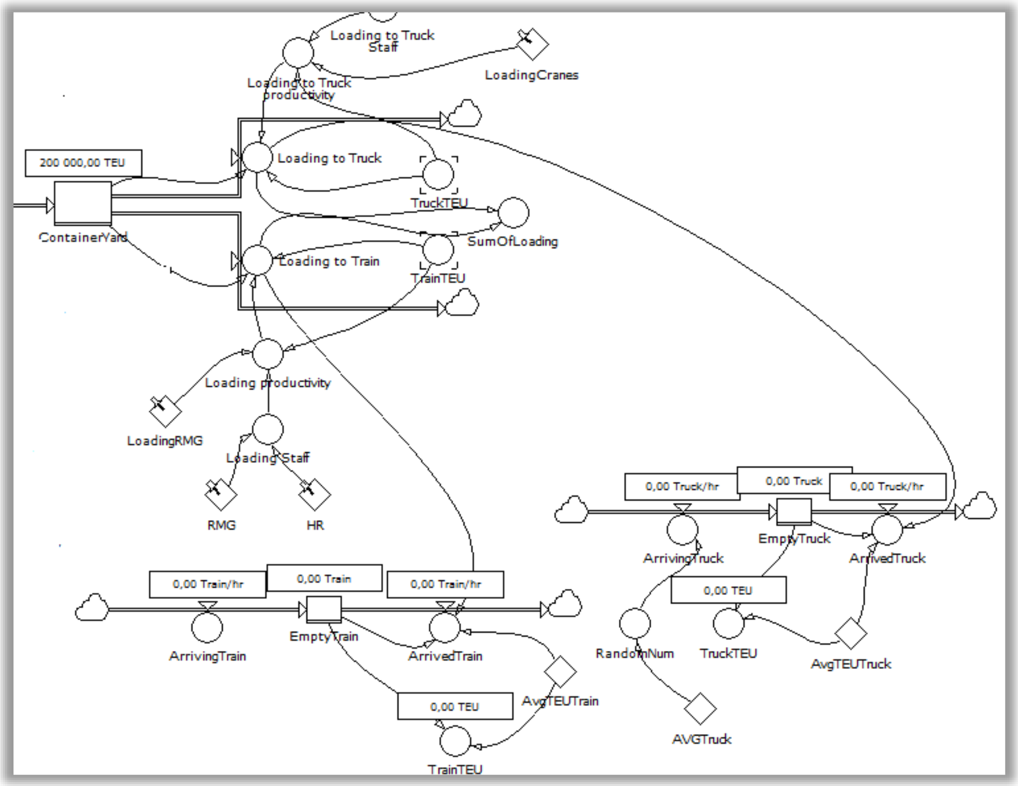

Figure 3: Coming and loading of trains and trucks

A separate flow is created for trains incoming, where in rate ‘ArrivingTrain’ it is defined the time shifts when empty trains arrive and a quantity of arriving trains per hour. The number of arrived trains is accumulated in level ‘EmptyTrain’. In auxiliary ‘TrainTEU’ counted containers the quantity of arrived trains by multiplying number of arrived trains from level ‘EmptyTrains’ with average number of containers per one ship from constant ‘AvgTEUTrain’. So, in auxiliary ‘TrainTEU’ there is the number of necessary containers, that have to be taken from container yard. Now there is the need to define loading productivity. For that the available number of rail cranes, human resources and productivity of one rail crane per hour are requested. All that data are stored in constants ‘RMG’, ‘HR’, and ‘LoadingRMG’. General loading productivity is in auxiliary ‘Loading productivity’: it is null if there are no train arriving, and it is equal to the real productivity if it is smaller than maximal loading productivity, or to this one if it is bigger (maximal productivity is the available loading staff multiplied with one rail crane productivity). Rate ‘Loading to Train’ is connected with level ‘ContainerYard’ and with auxiliaries ‘TrainTEU’, ‘Loading productivity’. Its task is to take off containers of container yard. So, that way happens loading to train procedure.

Truck loading scheme is similar with train loading scheme. Difference is in the logic of arrival. In auxiliary ‘RandomNum’ is used random function. The random function generates a series of random numbers that are distributed according to the uniform distribution, with a minimum value of min, and a maximum value of max . It’s mean that every day will arrive different number of trucks in interval between of defined min and max number.

In the following picture (Fig. 3) the simulator interface is represented and shows the real set up of the terminal.

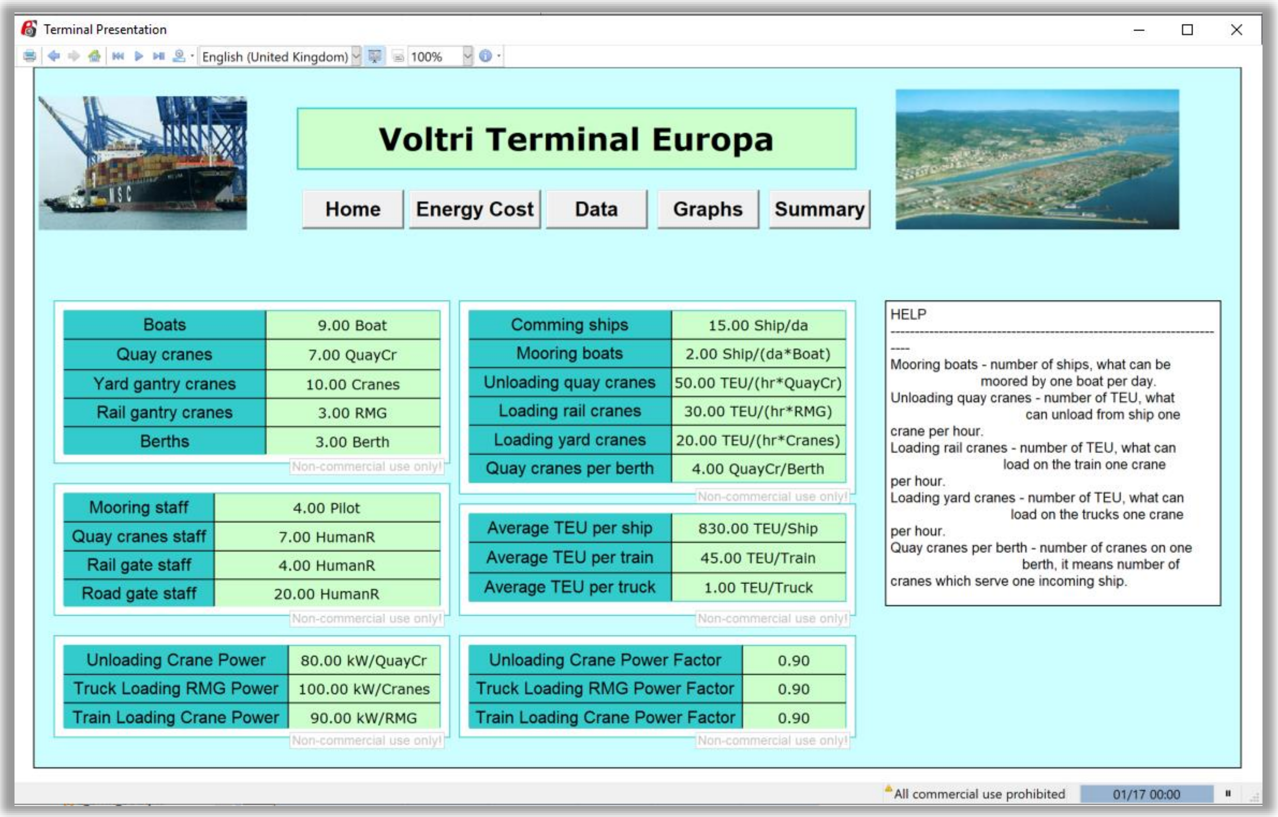

Figure 4: Model Operation set-up

4 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 simulated operation of the logistics center giving back information on costs owned by the logistics center. In the same time the tool is able to connect to the market exchange in order to analyze price trends on different markets, to do predictive analysis for the best market in the next 1-2 days and to show comparison between forecasted and real costs due to market choice.

In figures 4 and 5 the tool interface for Energy Costs Graphs and Power Graphs is represented.

For the predictive model [14] one of the fundamental purpose of the classical analysis of the time series [15 - 19] has been taken into account. The aim is to decompose the series in its components, isolating them for a better analysis. Besides, to be able to apply the stochastic approach to the historical series, it is necessary to eliminate the trend and the seasonality with the purpose to have a static process. The components of a historical series are usually the followings: trend, seasonality, cycle, residual or erratic. They can be tied up among them in additive way:

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

Where:

- Xt is the time series
- Tt is the trend
- Ct is the cyclic component
- St is the seasonal component
- Et is the error component

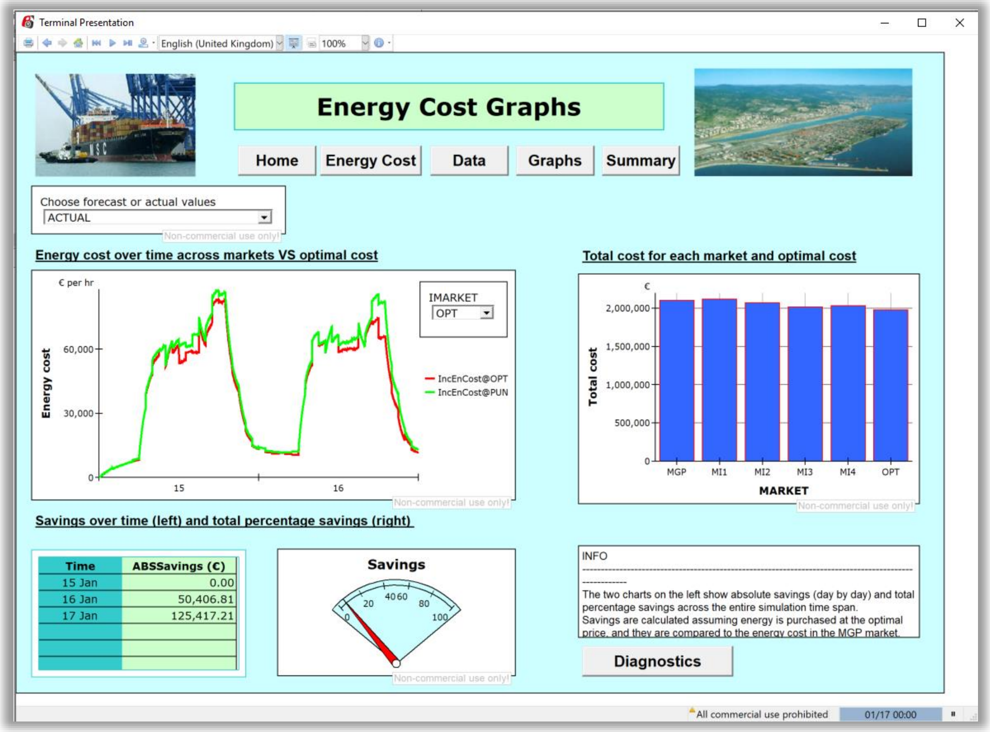

Figure 5: Energy Cost Graph

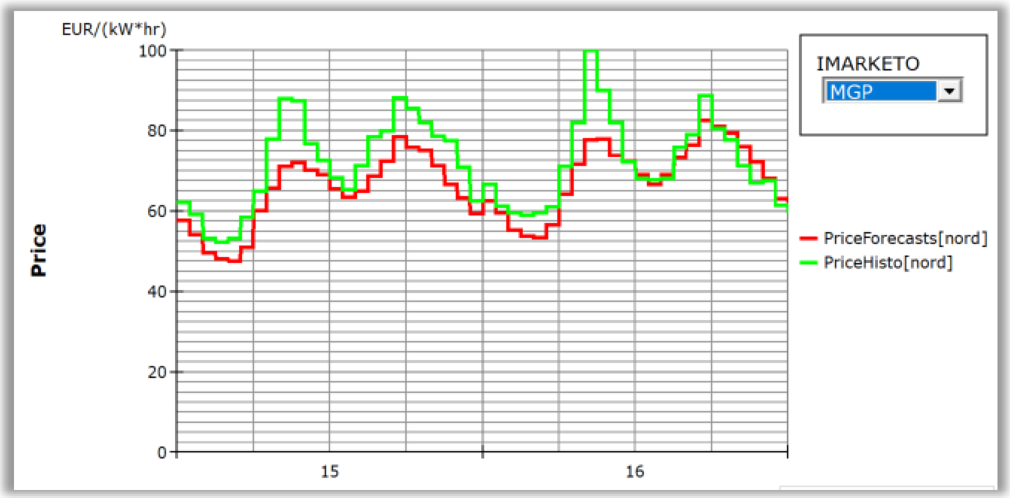

Figure 6: Power Consumption Graph

The importance of this tool is its capability to immediately show economic savings due to good market choices.

4.1 Model individuation

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 than 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 and research of the proper 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).

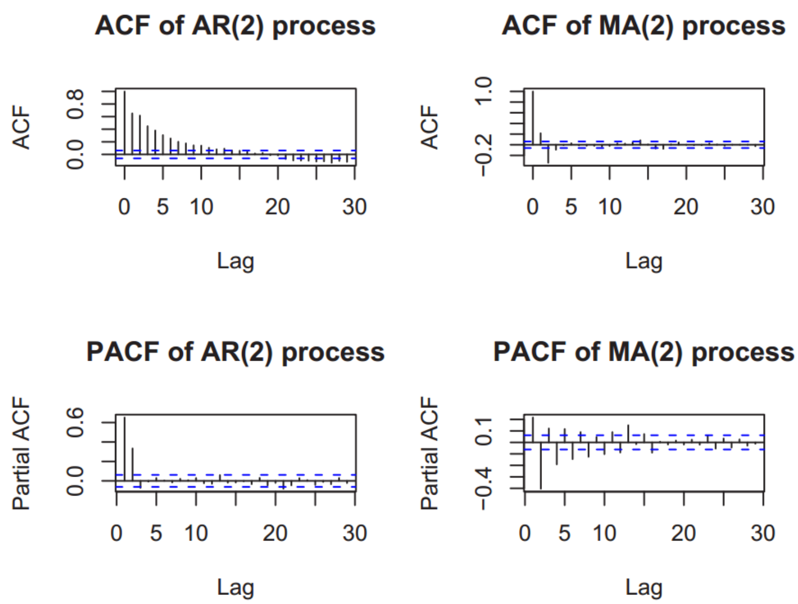

Figure 7: Partial and global auto-correlation Graphs

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. And 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 ($x_{t+1}; x_{t+2}; \dots ; x_{t+k-1}$) that are in the middle. Figure 7 shows the autocorrelation graphs for two sample processes (generated with the code in C.3): an AR (2) and an MA (2). It can be noted that only the ACF gives useful information for the MA process and that only the PACF gives information for the AR process.

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 Ljung-Box test the errors must be truly quite random, as generated by a White Noise trial.

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.

$X^\wedge_{t+l}$ 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.

4.2 Market analysis

Purpose of this section is to implement the theoretical models of the previous section in order to find the model that best fits in forecasting price trends in the Italian electricity market in the very short term (24 hourly prices for one or 48 for two days). First, the aspects that influence the market will be described, then will be analyzed the historical series of the day before market (MGP) prices; based on its characteristics, the appropriate parameters will be chosen and the model obtained will be compared with other similar models. Subsequently, a residual analysis and an analysis of forecasting capacity will be performed.

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. Most of the past studies employ low frequency measurements based on a daily or weekly reference price, neglecting much of the information. The very fine data granularity (one price per hour) shows a high volatility of the price in the long run period. The main causes of these fluctuations during the day are:

• impossibility of storing large quantities of energy and therefore 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.

From the first autocorrelation analysis [20-22], and even from the daily chart (example in Figure 8) of prices a strong seasonal seasonality can be noticed, due to the hours of productive activities. Figure 8 highlights two peaks: one in the time slot of 8:00 and another in the range from 17:00 to 18:00; these peaks, more or less accentuated, are present for all the days considered. Moreover, there is a weekly seasonality mainly due to the days of rest from productive activities and the demand for them (for example, weekly data in Figure 9).

Figure 9 shows 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.

Considering only these factors one can imagine a price curve that rises in the productive hours and falls during night hours. However, all the factors influence in an unpredictable way the curve. However, we can identify at least three different periodicity patterns:

- Daily;
- Weekly;
- Annual.

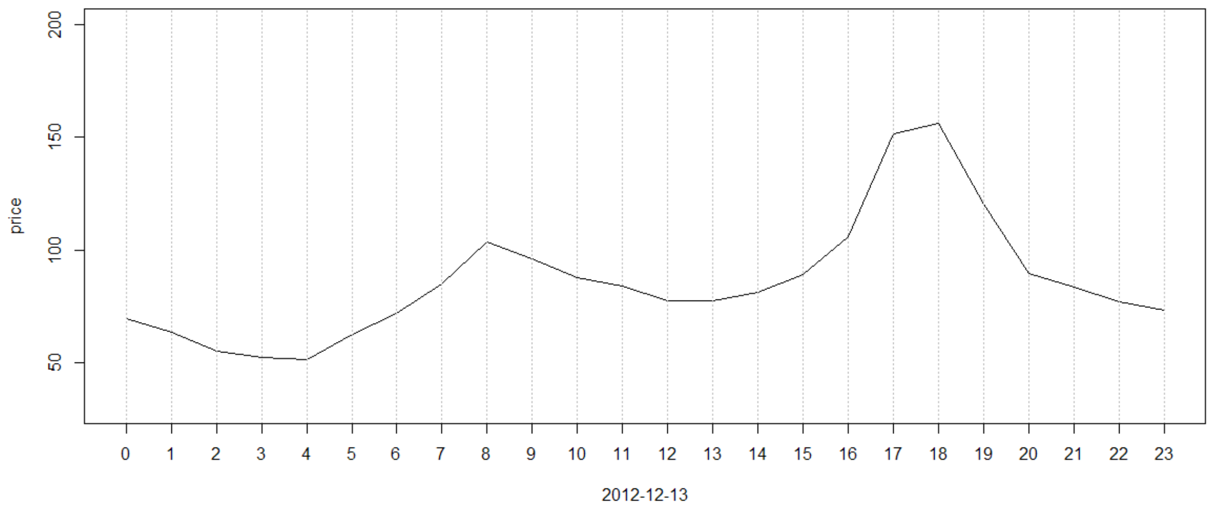

Figure 8: Prices per hour in a day

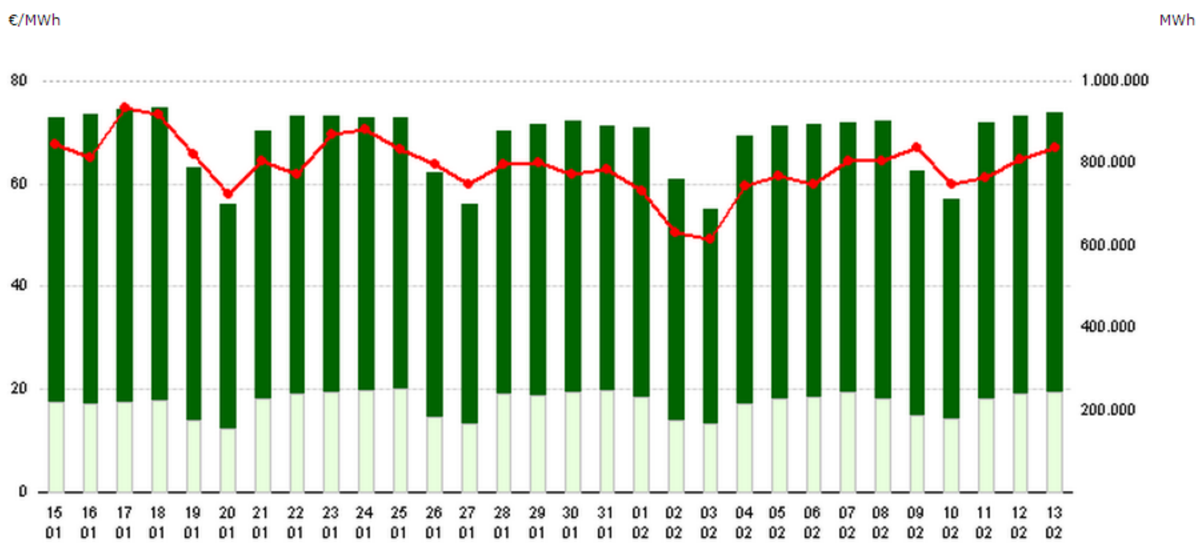

Figure 9: Prices in one month

4.3 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). For simplicity, we will consider 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 represented in the graph in Figure 10.

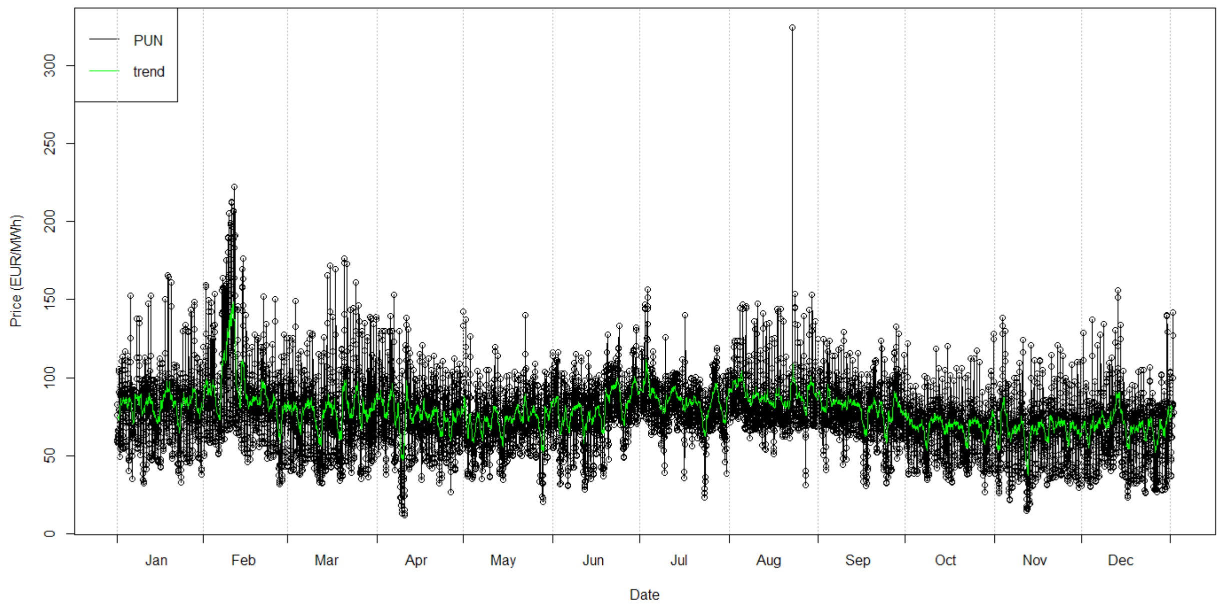

Figure 10: Real price data

Figure 11 shows the graph of the first 21 days, i.e. 504 prices. The data were preprocessed to verify that the series was stationary:

• the evening peak of August 21st was removed, which recorded the highest price (from more than 5 years), as seen in Figure 12, and has been replaced with the price of the same time the following day.

• 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 (useful with implementations of the algorithms for the calculation of the coefficients of the ARIMA models) was carried out a first-order differentiation, in Figure 12. In practice, 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.

• so, the non-seasonal differentiation parameter will be d = 1

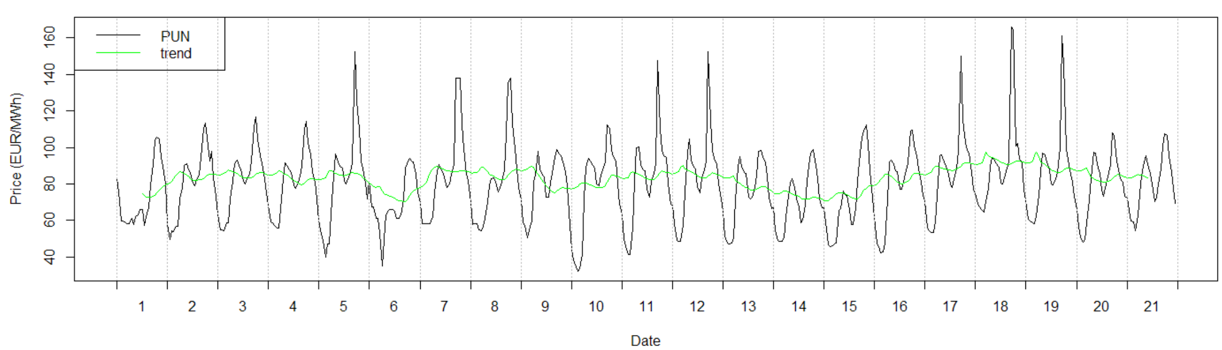

Figure 10: Real price for the first 21 days of the considered month

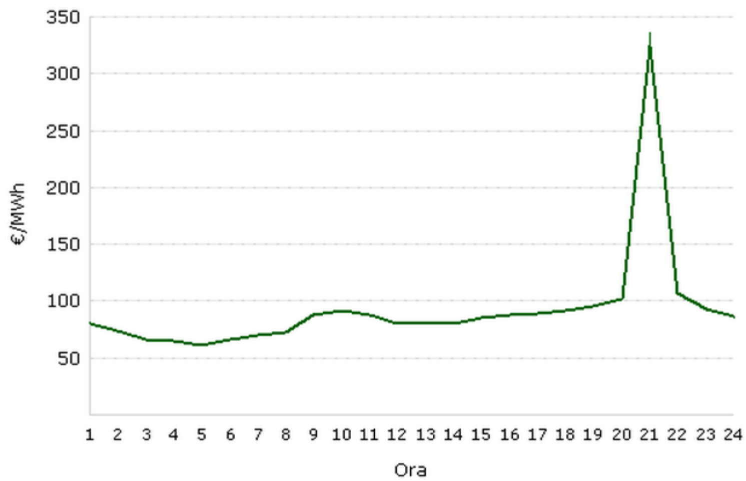

Figure 11: Focus on hourly price of 21 august

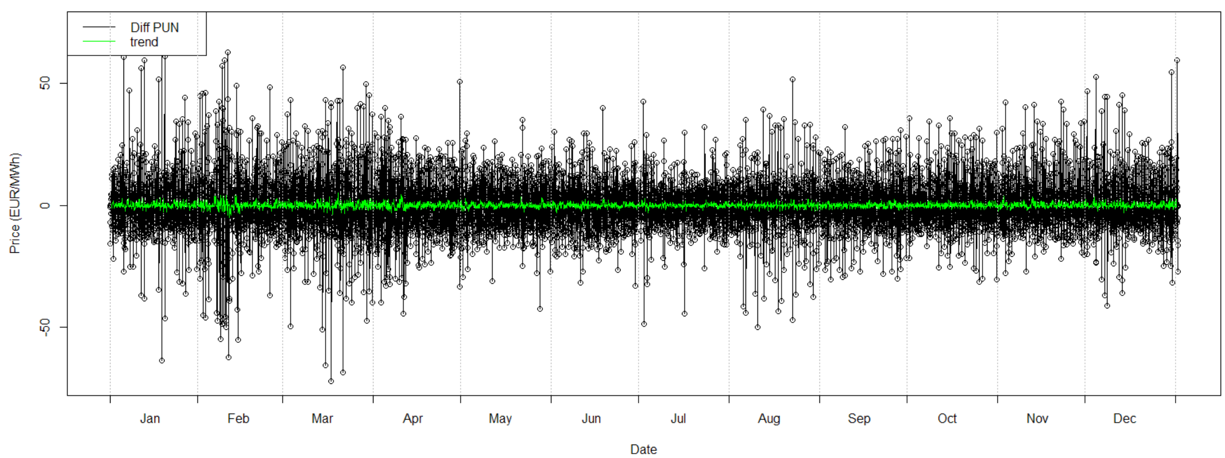

Figure 12: Prices differentiation diagram

From the data processed in this way, it is possible to analyze the graphs of the global and partial autocorrelation functions, in Figure 13. 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 $q = 0$.

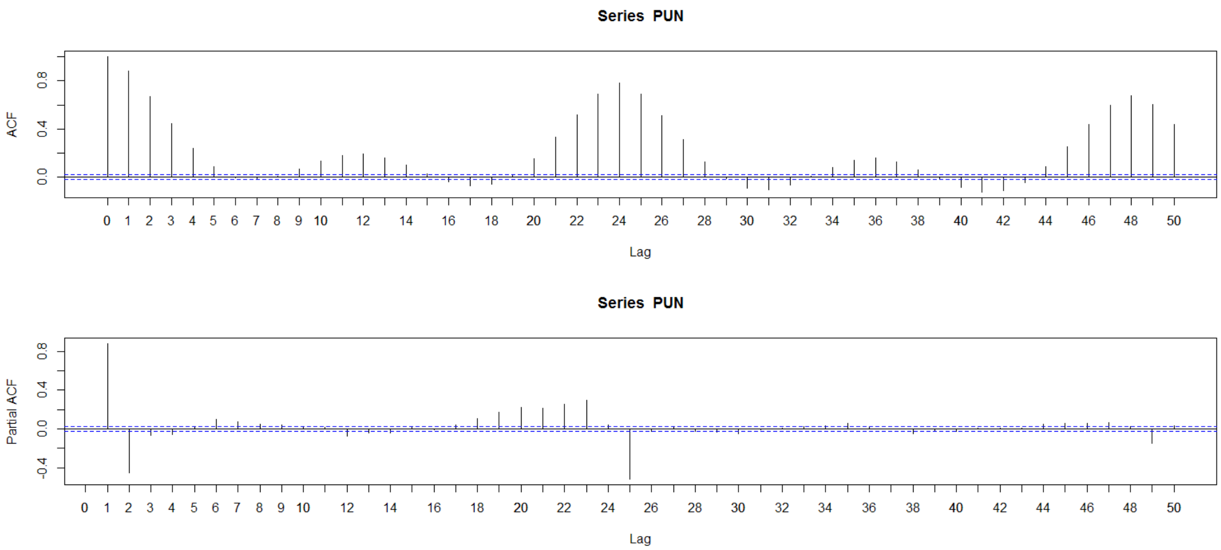

Figure 13: Global and partial auto-correlation diagrams

4.4 Residual analysis

The purpose of this section 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 14 shows the decomposition of only the first 504 prices of the year.

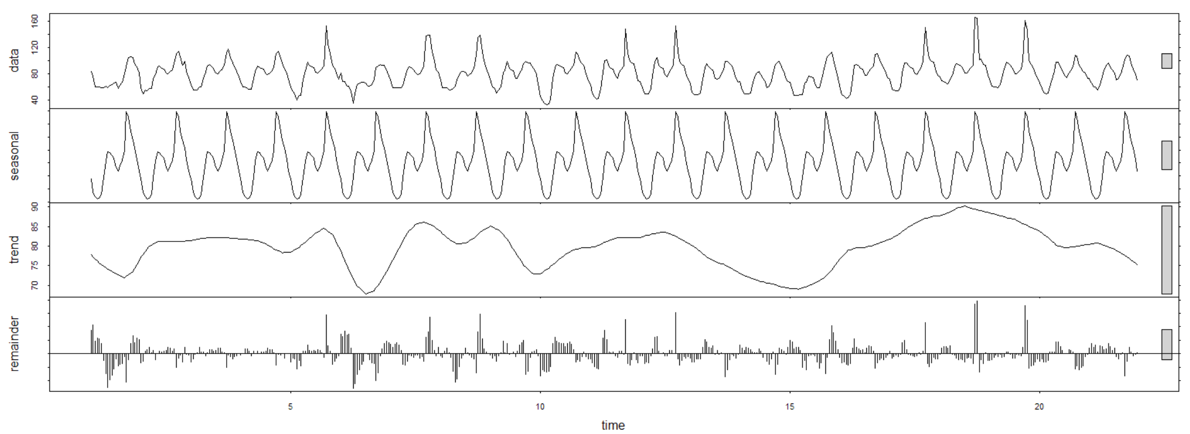

Figure 14: Decomposition of hourly prices in first 241 days

By plotting the global and partial autocorrelation diagram of the residuals, in Figure 15, 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.

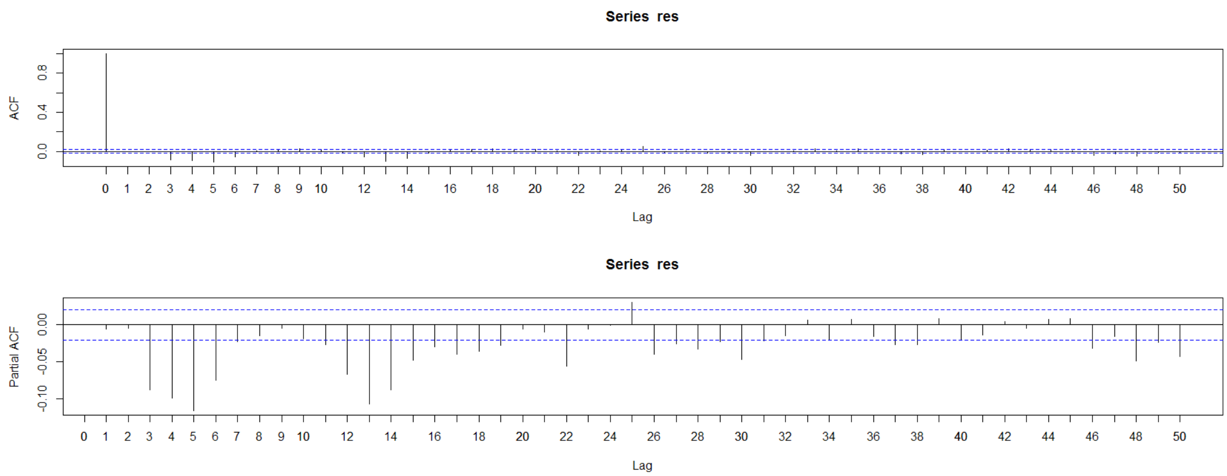

Figure 15: Decomposition of hourly prices in first 241 days

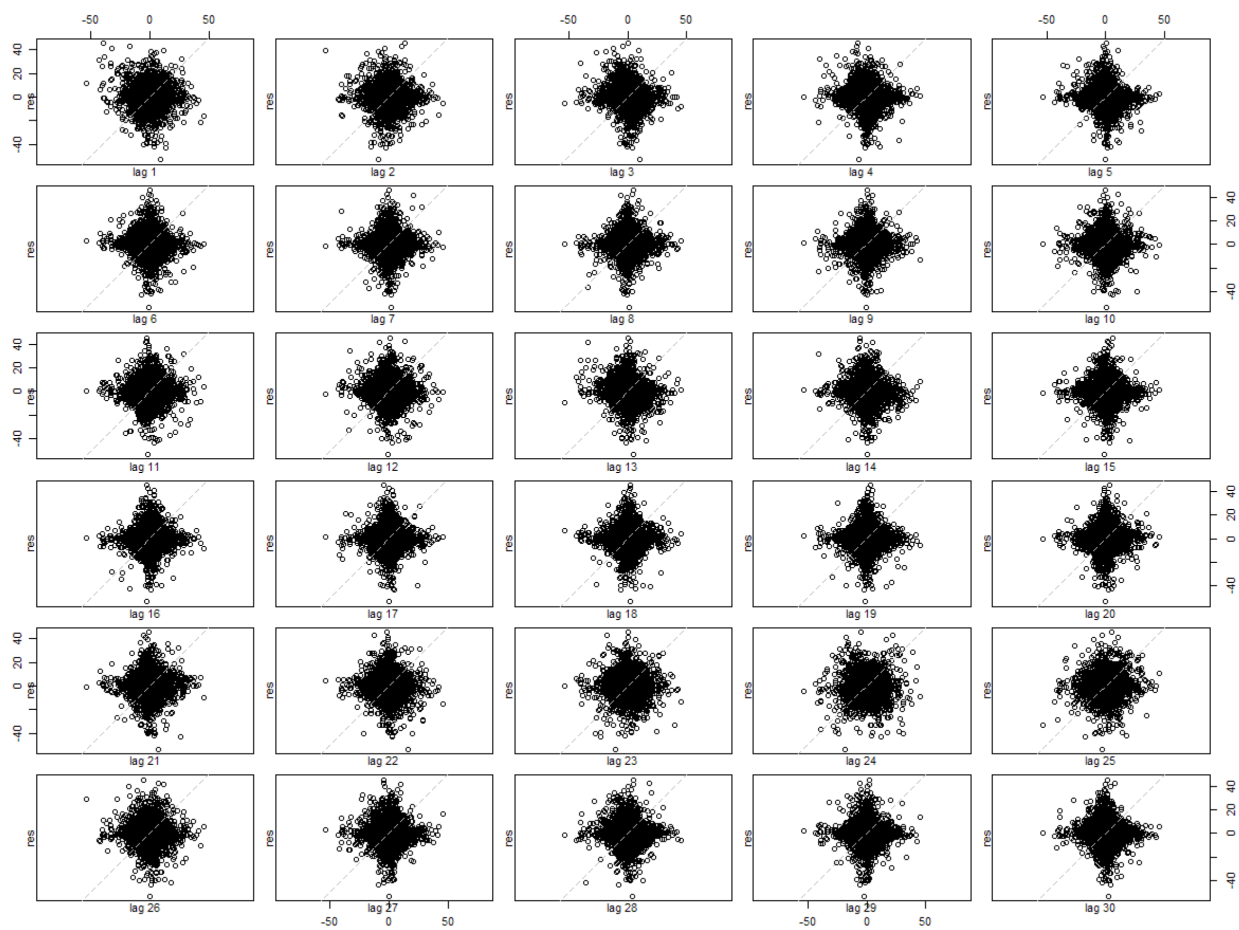

Figure 16: Self-dispersion diagrams for hourly prices

From the self-dispersion graphs can be observed the dispersion between the original series and the same series retarded of a lag, in Figure 16 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.

4.5 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:

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

Where $\overline{Xt}$ is the average price of the day and $\widehat{Xt}$ s the estimated hourly price. In Table 1 the detail daily MDEs in the second half of January and the first half of February.

Table 1: 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

Figure 17 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.

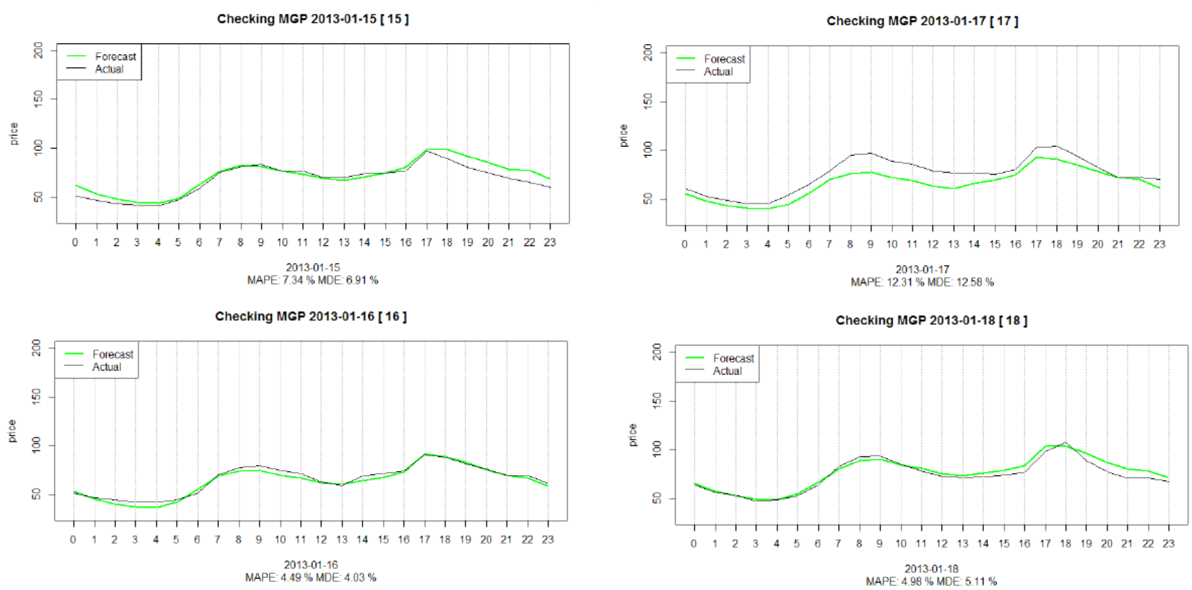

Figure 17: Prevision in comparison with real data for four days

In general, the results are good, and the forecasts particularly different from reality can be explained by external unpredictable phenomena 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.

5 CONCLUSIONS

With this work is has been addressed the problem concerning energy supply during the planning phase of an intermodal logistics center. 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 an 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 e 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.

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