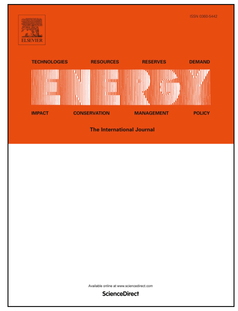
Accepted Manuscript



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PII: S0360-5442(17)30238-4

DOI: 10.1016/j.energy.2017.02.064

Reference: EGY 10357

To appear in: *Energy*

Received Date: 12 November 2016

Revised Date: 16 January 2017

Accepted Date: 12 February 2017

An integrated model for risk management in electricity trade

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ABSTRACT

This paper presents an integrated model for risk management of electricity traders. It integrates the Unit Commitment (UC) problem, which provides the power generation units' dispatch and the electricity price forecasting of a power system, with artificial neural network (ANN) models, which provide electricity price forecasting of a neighbouring power system by incorporating a clustering algorithm. The integrated model is further extended to estimate the traders' profitability and risk, incorporating risk provisions. The integrated model is applied in bi-directional trading between the Italian and Greek day-ahead electricity markets. The UC and neural network models

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provide forecasts of the wholesale electricity price in Greece and Italy respectively. The model attributes a confidence level of the price forecasts, depending on the data clustering and the forecasting performance of each model. The integrated model identifies periods with high price margins for trading for each power flow, aligned with a forecasting confidence and a risk level. The integrated model can provide price signals on the profitability of traders and useful insights into the risk of traders.

Keywords: Electricity trade; Electricity price forecasting; Risk; Unit commitment problem; Artificial neural networks; Day-ahead market

1. Introduction

A vital priority in European Union's energy policy is the integration of its electricity markets. This will facilitate the use of interconnections among national power systems, increasing the power flows and identifying the bottlenecks among them. Investing in such interconnections is important, as in the long-term, they lead in the whole energy system cost reduction. Boffa et. al., [1], estimated that investments in the interconnections of the Italian power system can provide benefits, as even a small increase of the interconnections' transmission capacity could considerable mitigate consumers' costs.

The electricity traders are very important market players towards enhancing market coupling and overall energy system cost minimization. The traders pursue economic benefits, identifying their strategy based on price signals from interconnected power markets. However, they face considerable risks. Dyner et. al. [2] concluded that the participation of traders in the Colombian market increases as its transparency increases and as long as traders are increasing their understating of the market risks.

Shakouri et. al. [3], developed a model for economically optimization of electricity trade between the Turkish and Iranian power systems, quantifying the supplementary benefits of peak shaving. Boroumand et. al. [4], analysed the electricity retailers' risks. The paper compares different intra-day portfolios of hedging, using VaR and CVaR risk measures. It concludes that intra-day hedging is superior over daily hedging. Antweiler [5], developed a theoretical model of cross-country electricity trading, providing evidence from the power systems of Canada and USA. They concluded that identifying the bottlenecks and integrating North America's power systems into a continental "supergrid" can provide economic benefits. Another paper [6] has led to similar conclusions, applied to Europe, namely that cross-border electricity trade facilitated by privatization processes, can transform national markets into a continental "supergrid" for Europe. The paper focused on which are the main determinants of electricity trade among the European power systems, providing evidence that privatisation enhances power flows and transactions in most cases.

The enhancement of electricity trade strongly depends on the interconnections capacity and on the capability to forecast wholesale electricity prices. However, the latter is a complex task, where different methodologies compete on their capability to provide robust price forecasts. The literature review on electricity price forecasting, especially for the Italian and Greek day-ahead markets is not extensive. A recent paper [7] explored the potential of Artificial Neural Network (ANN) based models on the day-ahead electricity price forecasting in the Italian market. It provided a comprehensive review in the literature and proposed ANN and hybrid ANN models, working with no pre-processed data and implementing a clustering algorithm, which separates historical data in well-separated and homogeneous groups. Gianfreda and Grossi, [8-9], examined the electricity prices of the Italian wholesale market, focusing on providing evidence among the prices of the different zones. The authors implemented Reg-ARFIMA–GARCH models to examine the effect -on the Italian wholesale electricity market price- of critical variables, such as market shares of dominant players, power generation technology types and transmission systems congestions. Bosco et. al. [10], implemented an empirical analysis on the prices of the Italian electricity market. It developed periodic AR-GARCH models, providing evidence on their superior performance compared to more traditional approaches. Bollino and Polinori [11], examined the existence of contagion in electricity markets, focusing only on pure contagion relationship in the Italian Power Exchange (IPX) at the Italian regional level. Petrella and Sapio [12], applied SARMAX and EGARCH models to examine the influence of future products, market competition and white certificates on the evolution of the Italian day-ahead electricity prices. It provides evidence electricity price fluctuations are affected from forward and cfd products, as well as from white certificates' products trading. Although, the ANN models as well as time series models are very useful, they are not robust enough for electricity price forecasting [7], as they usually do not consider critical techno-economic parameters, such as fuel and CO2 prices, merit order of generation plants, renewables and hydropower capacity, market participants' strategies, network congestion and others. Those parameters are usually tackled with more detailed techno-economic models, such as those elaborating the Unit Commitment (UC) problem or those that focus on the strategy of market players [13], which provided an analysis of the Italian day-ahead market, focusing on the role and bidding policy of the dominant market player, namely Enel or those that focus on the competitiveness of the different technology and fuel types for power generation, quantifying also the influence of renewables generation on the day-ahead electricity prices in the Italian day-ahead market [14].

The UC problem identifies the power units' dispatch considering their bidding strategy, their operational and maintenance costs, their ramping capacity, their capability to provide ancillary services and other techno-economic criteria. Liu and K. Tomsovic, [15] proposed a robust unit commitment model, incorporating the price elasticity uncertainty. Bakirtzis et. al., 2014 [16] present a unified unit commitment and economic dispatch model, applicable for a 24-hour time horizon, while Andrianesis et. al., 2011 [17] present a medium-term unit commitment problem, applicable for a longer horizon of several days, aiming to capture the effects of techno-economic characteristics of the thermal units, such as the start-up times and costs. Biskas et. al. [18], examined the forthcoming market coupling/integration of the Greek with the Italian electricity market, implementing the integration of a power exchange (PX), namely the Italian wholesale market and a power pool, namely the Greek wholesale market. Koltsaklis et. al., 2014 [19] present a spatial multi-period long-term energy planning model, identifying the power generation technologies, the fuel types, the plant locations that optimally satisfy electricity demand and environmental constraints, while Koltsaklis et. al. [20] present a model that integrates a mid-term energy planning model, which implements annual generation and transmission system planning, with a unit commitment model, which performs the simulation of the day-ahead electricity market.

From the above analysis, it derives that the risk of traders from the participation in the cross-border electricity trade has not been extensively examined, especially in case of the Italian-Greek day-ahead markets, which have not yet been coupled, as the case of Italian-Slovenian markets [21]. Electricity trading in the Italian-Greek interconnection, as well to the other interconnections of Greece, is not related -for the time being- to the development of a coordinated model implementing the same market algorithm among the interconnected systems, but to the capability to provide robust forecasts of electricity prices on the two day-ahead markets, Italy and Greece. The paper presents an integrated model, integrating ANN with UC models, providing and elaborating price forecasts towards identifying the risk of traders in the interconnected markets. The applicability of the integrated model concerns all physically interconnected power markets that are not market coupled, through a common market algorithm. In such a case, the development of a model applying the common market algorithm [22] would provide more robust results and price signals for market participants.

This paper integrates a Unit Commitment (UC) model, which provides the power generation units' dispatch and the electricity price forecasting of a power system with hybrid artificial neural network (ANN) models that incorporate a clustering algorithm, towards electricity price forecasting of a neighbouring power system. The integrated model is further extended to estimate the traders' profitability and risk under different trading strategies. The integrated model is applied in bi-directional trading between the Italian and Greek day-ahead electricity markets. The highlights of the paper are: (i) integration of Unit-Commitment problem with ANN based models, (ii) clustering of the data to identifying periods with increased certainty on the day-ahead electricity price forecasting, (iii) identification of periods with high price margins for electricity trade iv) provision of price signals on the profitability of traders (iv) provision of useful insights into the risk of traders. Section 2 presents the methodology applied in this work, while Section 3 provides the main data of the case study. The main results of our study are given in Section 4, and Section 5 discusses upon some concluding remarks

2. Methodology

Methodologically, this work is an integrated approach which combines a unit commitment model for day-ahead price forecasting of a power system with ANNs based models for day-ahead price forecasting of a neighbouring power system. This approach is based on previous works [19-20, 23], concerning the unit commitment problem, and a previous work [7] concerning the artificial neural network models. The integrated model is further extended to estimate how the traders' profitability is affected from the cross-border electricity trade.

2.1 Unit Commitment model for a power system

The UC model concerns the optimum operation of a power system at a daily period. Therefore, the model's objective function is represented by Equation (1).

$$\boldsymbol{Min}\ Cost^{daily} =$$

$$\overbrace{\sum_{g\in(G^{hth}\cap G^{z})}\sum_{z\in Z}\sum_{b\in B}\sum_{t\in T}\left(pb_{g,b,m,t}\cdot CB_{g,b,t}\cdot L_{z,t}\right)}^{Marginal\ production\ cost}$$

$$+\overbrace{\sum_{n\in N^{z}}\sum_{z\in Z}\sum_{b\in B}\sum_{t\in T}\left(imb_{n,b,t}\cdot CIP_{n,b,t}\cdot L_{z,t}\right)}^{Power\ imports\ cost}$$

$$-\overbrace{\sum_{n\in N^{z}}\sum_{z\in Z}\sum_{b\in B}\sum_{t\in T}\left(exb_{n,b,t}\cdot CEP_{n,b,t}\right)}^{Power\ exports\ revenues} \quad (1)$$

$$-\overbrace{\sum_{e\in E^{z}}\sum_{z\in Z}\sum_{b\in B}\sum_{t\in T}\left(pmb_{e,b,t}^{pum}\cdot CPM_{e,b,t}\right)}^{Pumping\ load\ revenues}+$$

$$\overbrace{\sum_{g\in G^{hth}}\sum_{t\in T}(x_{g,t}^{sd}\cdot SDC_g)}^{Shut-down\ cost}$$

$$+\overbrace{\sum_{g\in G^{hth}}\sum_{t\in T}\left[\left(r1_{g,t}^{up}\cdot RC1_{g,t}\right)+\left(r2_{g,t}^{up}+r2_{g,t}^{down}\right)\cdot RC2_{g,t}\right]}^{Reserves\ provision\ cost}$$

The UC problem considers the energy offers and demand declaration of market participants, towards identifying the System Marginal Price $SMP_{s,t}$ for subsystem $s\in S$ and time period $t\in T$. Those offers are restricted by the techno-economic characteristics of each unit. Figure 1 presents the energy supply offer for a thermal unit u, compared to its incremental cost and its minimum variable cost, for different power outputs, among unit's technical minimum P_u^{min} and technical maximum P_u^{max}.

Insert Figure 1

The minimization of the objective function provides the System's Marginal Price (SMP), namely the system's wholesale electricity price. **Figure 2** represents the determination of the SMP, as the crossroad of aggregate supply and demand curves. The problem is modelled as a mixed-integer linear programming (MILP) problem, subject to constraints defined in a recent paper [23].

Insert Figure 2

2.2. ANN for day-ahead price forecasting of a neighbouring power system

The ANN models are applied for electricity price forecasting of a neighboring system $n\in N$. The ANN model incorporates clustering techniques for organizing time periods in different clusters. The implementation of clustering techniques aims at identifying the time periods with high certainty of forecasting. The confidence level

$CONF_{n,m,c,t}$ of price forecasting $SMPF_{n,t}$, is estimated considering the historical forecasting errors $ERRF_{n,m,c,t}$ for interconnected system $n \in N$, model $m \in M$, cluster $c \in C$ and period $t \in T$. The same logic is applied for the UC model price forecasts $SMPF_{s,t}$,, concerning the subsystem $s \in S$, introducing variables $CONF_{n,m,c,t}$ and $ERRF_{n,m,c,t}$.

A basic advantage of the applied ANN models, is that they use raw data, including many price spikes and null values. Therefore, it concerns a realistic operation of a power market. A Feed-Forward Neural Network was implemented, trained by the Levenberg-Marquard algorithm [24]. The number of hidden layers is 1 and the neurons in the hidden layer is 10. Both hidden and output layers use hyperbolic tangent sigmoid transfer function. The maximum number of training epochs was set to 100.

The implementation of clustering techniques as mentioned below, aims at identifying the time periods with high certainty of forecasting. A hybrid ANN mode is chosen [7] incorporating a topology of two general stages, as shown in Figure 3. The first stage concerns the elaboration of data and implementation of the clustering algorithm, while the second stage concerns the application of the neural networks for each cluster, by using K-means, the most common algorithm in demand patterns' problems [25]. The aim of the first stage is to formulate the data set into the suitable form for the clustering, towards obtaining meaningful and exploitable results from the clustering operation. This preprocessing stage aims at identifying similarities and trends of the daily price curves, by comparing their shapes. Through an iterative process, the algorithm tends to minimize the sum of squared errors and it terminates when there are no transpositions of patterns from cluster to cluster during the successive iterations. K-means partitions the training set matrix into k clusters. Hence, k ANNs are trained separately with the data of the corresponding clusters. The final forecasting error is calculated by considering the errors generated from each ANN.

Insert Figure 3

2.3. Traders profitability

We assume that the trader $r \in R$ is participating in the interconnection between subsystem $s \in S$ and the interconnected system $n \in N$.

Critical issues for trader's profitability is the price $SMP_{s,t}$, in system $s \in S$ and period $t \in T$, the price $SMP_{n,t}$, in interconnected system $n \in N$ and period $t \in T$, the price $TRA_{s,n,t}$, in the transmission rights explicit auctions for the interconnection between system $s \in S$ and interconnected system $n \in N$ for period $t \in T$, and the volume of electricity they trade $TRQ_{s,n,r,t}$, $TRQ_{n,s,r,t}$. from the system $s \in S$ to interconnected system $n \in N$ for period $t \in T$ and vice versa respectively/

Moreover, critical issues for trader's profitability are the robustness of the day-ahead price forecasts in the interconnected systems and the margin levels that satisfies the trader in order to participate.

The profitability of the traders is given from the following equations:

$$REVENUE_{s,n,r,t} = \left(SMP_{s,t} - SMP_{n,t} - TRA_{s,n,t}\right) \cdot TRQ_{s,n,r,t} \tag{2}$$

$$REVENUE_{n,s,r,t} = \left(SMP_{n,t} - SMP_{s,t} - TRA_{n,s,t}\right) \cdot TRQ_{n,s,r,t} \tag{3}$$

$$REVENUE_{r,t} = \sum_{s \in S} \sum_{n \in N} \left(REVENUE_{s,n,r,t} + REVENUE_{n,s,r,t}\right) \tag{4}$$

for each trader $r \in R$, for the interconnection between system $s \in S$ and interconnected system $n \in N$ for period $t \in T$. Equation 2 refers to the case where traders export electricity from system $s \in S$ to interconnected system $n \in N$, while equation 3 when the trader imports electricity in the same interconnection. In the above equations, we assumed that the system marginal prices incorporate all other costs, e.g. export and participation fees. So they represent the total cost in each border.

However, the actual profitability cannot be estimated ex-ante. In fact, the traders do not participate in all interconnections and do not trade the same volumes in each interconnection in all time periods. The trader evaluates its price forecasts $SMPF_{s,t}\cdot$ and $SMPF_{n,t}\cdot$ for the system marginal price in system $s \in S$ and the interconnected system $n \in N$ for period $t \in T$ respectively. For those forecasts, the trader has a confidence $CONF_{s,m,c,t}$ and $CONF_{n,m,c,t}$ respectively. Considering the confidence level, which differentiates based on the model $m \in M$ (UC or ANN) as well as on the cluster $c \in C$, the trader readjusts its price forecasts, based on a price adjustment factor $PADJ_{s,t}$, according to the following equations:

$$SMPF'_{s,t} = SMPF_{s,t} \cdot PADJ_{s,t} \;\; or \; SMPF_{s,t} \,/\, PADJ_{s,t} \tag{5}$$

$$SMPF'_{n,t} = SMPF_{n,t} \cdot PADJ_{n,t} \;\; or \; SMPF_{n,t} \,/\, PADJ_{n,t} \tag{6}$$

for each system $s \in S$ or interconnected system, model $m \in M$ and cluster $c \in C$ for period $t \in T$. The price adjustment factor $PADJ_{s,t}$, $PADJ_{n,t}$ depends on the confidence level $CONF_{s,m,c,t}$, $CONF_{n,m,c,t}$ of the price forecasts.

The confidence levels are given by the historical errors in forecasting for each system $s \in S$ or interconnected system, model $m \in M$ and cluster $c \in C$ for similar periods $t \in T$. Therefore, confidence are linked to the forecasting errors, as shown:

$$CONF_{s,m,c,t} = 100 - ERRF_{s,m,c,t} \tag{7}$$

$$CONF_{n,m,c,t} = 100 - ERRF_{n,m,c,t} \tag{8}$$

The equations (9-10) have two values, in order to decrease risk as describe below. The actual condition for participation depends on the estimated margin for the traders. The model incorporates a more conservative approach, concerning risk exposure, estimating this margin based on the following equation:

$$MARGIN_{s,n.t} = MIN\left(SMPF'_{s,t} - SMPF'_{n,t} - TRA_{s,n,t}\right) \tag{9}$$

$$MARGIN_{n,s.t} = MIN\left(SMPF'_{n,t} - SMPF'_{s,t} - TRA_{n,s,t}\right) \tag{10}$$

Which practically means that the model uses the lowest margin for all four cases, two for the price of $SMPF'_{s,t}$ and two for the price of $SMPF'_{n,t}$. If this margin is higher than an acceptable tolerance $MARG\_TOL_{r,t}$, different for each trader $r \in R$, then the trader decides to participate in the day-ahead cross-border trade. This is depicted in the model with the activation of a flag, $FLAG_{S,t}$

$$FLAG_{s,n,r,t} = 1, if \ \ MARGIN_{s,n,t} - MARG\_TOL_{r,t} > 0 \tag{11}$$

$$FLAG_{n,s,r,t} = 1, if \ \ MARGIN_{n,s,t} - MARG\_TOL_{r,t} > 0 \tag{12}$$

The robustness of the price forecasts affects also the quantities traded. Therefore, based on the confidence level of the price forecasts, the trader readjusts its quantities, based on a volume/quantity adjustment factor $QADJ_{s,n,t}$,$QADJ_{n,s,t}$, according to the following equations:

$$TRQ'_{s,n,r,t} = TRQ_{s,n,r,t} \cdot QADJ_{s,n,t} \tag{13}$$

$$TRQ'_{n,s,r,t} = TRQ_{n,s,r,t} \cdot QADJ_{n,s,t} \tag{14}$$

Therefore, the trader's revenue is estimated from the following equations, which consider the actual and not the forecasted day-ahead prices:

$$REVENUE'_{s,n,r,t} = (SMP_{s,t} - SMP_{n,t} - TRA_{s,n,t}) \cdot TRQ'_{s,n,r,t} \cdot FLAG_{s,n,r,t} \tag{15}$$

$$REVENUE'_{n,s,r,t} = (SMP_{n,t} - SMP_{s,t} - TRA_{n,s,t}) \cdot TRQ'_{n,s,r,t} \cdot FLAG_{n,s,r,t} \tag{16}$$

$$REVENUE'_{r,t} = \sum_{s \in S} \sum_{n \in N} \left(REVENUE'_{s,n,r,t} + REVENUE'_{n,s,r,t} \right) \tag{17}$$

The difference between the estimated $REVENUE'_{r,t}$, which considers the risk management provisions, and the $REVENUE_{r,t}$, where no provisions are taken into account, depicts the performance of the above mentioned risk strategy for the trader.

$$RISK\_PER_{r,t} = \frac{\left(REVENUE'_{r,t} - REVENUE_{r,t} \right)}{\left| REVENUE_{r,t} \right|} \tag{18}$$

Similarly, a volume/quantity performance indicator is estimated, showing the change in quantities traded:

$$QUAN\_PERF_{r,t} = \frac{\left(QUANTITY'_{r,t} - QUANTITY_{r,t} \right)}{QUANTITY_{r,t}} \tag{19}$$

The forecasted prices in practice might deviate from the actual prices or might have different forecasting error from the historical forecasting errors, used as assumption in the model. The consideration of the actual day-ahead prices, as well the traded volumes, provides the actual revenue margin. Considering that, the traded volumes have been estimated in equations 13-14 based on historical forecasting errors, the actual revenue margin inherits the risk of the deviation between the actual and historical forecasting errors. The actual revenue margin is being estimated in the following equations:

$$REV\_MARG'_{s,n,r,t} = \sum_{s \in S} \sum_{n \in N} \frac{\left((SMP_{s,t} - SMP_{n,t} - TRA_{s,n,t})TRQ'_{s,n,r,t}\right)}{\left(TRQ'_{s,n,r,t}\right)} \tag{20}$$

$$REV\_MARG'_{n,s,r,t} = \sum_{s \in S} \sum_{n \in N} \frac{\left((SMP_{n,t} - SMP_{s,t} - TRA_{n,s,t})TRQ'_{n,s,r,t}\right)}{\left(TRQ'_{n,s,r,t}\right)} \tag{21}$$

3. Case study

The paper examines the trade among two neighboring systems, namely the Southern Italian zone (SUD) and the interconnected Greek power system. The interconnected Greek power system, simulated with the UC model, considers the data published in the monthly energy report of LAGIE of June 2016 [26]. The main operational and economic characteristics of the installed units of the Greek power system are available in our previous contributions [19-20].

The data used for the Italian day-ahead market is described in a recent work [7]. The ANN models are used for price forecasting of the Southern Italy zone (SUD), based on data from the Italian power exchange [27]. The available data set used, cover the period between 2012-2014, as training period and 2015 as test period for validating the model. The latter set determines the optimal ANN configuration. The clustering is used to partition the initial training set to training subsets (clusters). Each subset contains training patterns with more similar characteristics compared to the patterns of the rest clusters. Using this approach, we involve 4 FFNN, 1 for each cluster. This leads to better training, since each FFNN is trained with most correlated patterns, i.e. the patterns of each cluster are more similar than those of the other clusters. We selected 4 clusters via a trial-and-error process. With 4 clusters, the overall Mean Absolute Percentage Error (MAPE) is minimal. Table 1 provides the decomposition of clusters of the selected ANN model. Clusters 1-4 represent 26%, 35%, 26% and 13% of all test patterns (initial test data set) respectively. Clusters 1 and 2, with lower historical forecasting error as will be shown in the following section, concern mainly central weekdays (Tuesday-Thursday) and some of the rest weekdays (Fridays and Mondays), while cluster 4 concern Sundays, except for the last Sunday which is grouped with Saturdays and some weekdays (Mondays and Fridays) in Cluster 3.

Insert Table 1

The explicit auctions for the transmission rights for the Italian-Greek interconnection is implemented at the Joint Allocation Office [28], which is a joint service company of twenty Transmission System Operators from seventeen countries. for implementing auction. For the needs of our study, we used the published data for the daily auctions of July 2016. Therefore, in our model we assume that the trader knew the auction results of that day.

4. Results and discussion

This section provides the results from applying the integrated model. As mentioned above, the price forecasts are readjusted based on the confidence level for each forecast. Table 2 presents the Price (PADJ) and volume/quantity (QADJ) adjustment factors used in this study, which are applied to adjust the price forecasts and the quantities to be traded respectively, depending on the confidence level (CONF) of the day-ahead price forecasts. For the needs of our study we used data of July 2016. For the Greek system, where the UC model is implemented we estimate, based on the validation of the model, that the forecast errors are less than 5% for all examined time periods and therefore they do not lead to price forecast readjustments. For the Italian system, the time periods are organized in four clusters. The different clusters have different price forecasting errors, namely 10.78%, 12.43%, 37.09% and 37.89% respectively, based on their evaluation. The overall forecast error is 21.75%, high relevant to the UC model. Those forecasting errors, per time period are represented in Table 3. For simplicity reasons, the time periods for the UC model are organized in one cluster, compared to four for the ANN model of the Italian market. Table 4 includes the average hourly values of the main assumption used in the integrated model, namely the day-ahead forecast prices in the Greek and Italian SUD zones, the prices of the transmission rights in both directions of electricity trade between Greece and Italy, the margin which satisfy the trader, as well as the quantity traded in each direction, in case the trader does not consider any risk provision.

Insert Tables 2, 3 & 4

Figure 4 presents typical System Marginal Prices in Italy (SMP_{IT}) and Greece (SMP_{GR}), as well as the Transmission Rights prices from the daily auctions for trade from Italy to Greece ($TRA_{IT,GR}$) and vice versa ($TRA_{GR,IT}$). The power flow of the cable is mainly from Italy to Greece, which leads to some considerable price of the transmission rights for this direction. Although the Italian wholesale market has higher prices for some hours compared to the prices of the Greek wholesale market, the transmission rights for exports from Greece to Italy have usually zero values. This creates some profitability cases for traders, considering that they follow a risk strategy, as described in this paper.

Insert Figure 4

For the needs of our study, we consider that the trader is participating in cross-border trade with an average volume of 10 MWh per each hour. This leads to relevant profitability ($REVENUE_{IT,GR}$, $REVENUE_{GR,IT}$), per each direction when no risk provisions are considered, estimated by the equations (7-8). In case of considering the risk strategy, described in equations (10-19), an updated profitability is estimated from equations (20-21). Figure 5 presents the average trader's profitability with risk provisions ($REVENUE'_{IT,GR}$, $REVENUE'_{GR,IT}$) compared to this without risk provisions ($REVENUE_{IT,GR}$, $REVENUE_{GR,IT}$), per each direction in trade among Italy & Greece.

Insert Figure 5

The consideration of risk provisions is not affected only the profitability, but also the quantities traded, which are estimated by equations (18-19), considering the quantity adjusting factors but also the flag, from equations (16-17) for deciding the trader's participation based on the comparison of the estimated margin and the margin tolerance that satisfies the trader. For simplicity reasons, in our study we consider that value of MARG_TOL is zero. Figure 6 presents the average volume/quantity traded with risk provisions ($QUANTITY'_{IT,GR}$, $QUANTITY'_{GR,IT}$) compared to this without risk provisions ($QUANTITY_{IT,GR}$, $QUANTITY_{GR,IT}$), per each direction in trade among Italy & Greece. The graph shows, that the trader, adopting a more conservative approach, is eliminating the chance for losses. At the same time, the trader has profitability in selected hours in both directions. There are time periods, that a more aggressive trading approach, namely without risk provisions, could lead to higher margin in one of the two directions. However, the overall performance of the trader for each direction, is more profitable when the trader incorporates the above described risk strategy.

Insert Figure 6

When considering that the trader is participating in both directions, then an overall profitability is estimated by equation (8), when risk provisions are not taken into account and equation (22), when they are considered. Figure 7 presents the average trader's overall profitability with risk provisions ($REVENUE'_{IT,GR}$, $REVENUE'_{GR,IT}$) compared to this without risk provisions ($REVENUE_{IT,GR}$, $REVENUE_{GR,IT}$) for cross-border trade among Italy & Greece. The overall performance of the trader, concerning its profitability, is that the trader has increased profitability compared to a trader with no risk provisions. The graph shows that trader, with risk provisions, decides to participate with reduced quantities in different hour blocks, hours 1-6 for exports from Italy to Greece and hours 8-13 for exports from Greece to Italy. This shows that the trader has a higher flexibility in trading, compared to the results of the daily auctions of transmission rights, which depicted that traders are strongly interested for trading only in one direction, exports from Italy to Greece.

Insert Figure 7

The implementation of the risk management strategy, leads to an increase in profitability performance. This is depicted in the evolution of the indicator, estimated in equation (23). Figure 8 presents the evolution of the risk performance indicator, per direction of trading ($RISK\_PERF_{IT,GR}$, $RISK\_PERF_{GR,IT}$) and in total (RISK_PERF), for cross-border trade among Italy & Greece, when risk provisions are considered. The graph shows that the risk performance indicator has been increased by 147.3% in total, having fluctuations from -59.3% to +736.8% in the evolution of the relevant indicators for each direction. The participation of traders in cross-border trading without risk provisions, inherits considerable risks for significant losses.

As mentioned above, the incorporation of risk provisions, leads to significant decrease in traded quantities. Figure 9 presents the evolution of the volume/quantity performance indicator, per direction of trading ($QUAN\_PERF_{IT,GR}$, $QUAN\_PERF_{GR,IT}$) and in total (QUAN_PERF), for cross-border trade among Italy & Greece, when risk provisions are considered. The decrease is -77.4% on average, fluctuating between -69.3% and -87.3%. The fact that the model decides a reduction for all time periods is related to the fact that forecasting errors of the ANN are above the confidence level of 5%, which would lead to zero quantity adjustment. Therefore, the incorporation of risk provisions leads to considerable decrease in trading volumes and consequently decreases the liquidity needs for the traders.

Insert Figures 8 & 9

As mentioned in section 3, the actual revenue margin of the traders depends on the actual prices and the traded volumes, as decided to participate in the markets, through the implementation of the risk provisions. Figures 10-11 present the hourly average revenue margin for each direction and in total, when considering the risk provisions or not. Although, there exist at a daily level several time periods where the strategy with no risk provisions provide higher revenues, Figures 10-11 show that the risk strategy provides a higher margin for all time periods on average for the examined month.

Insert Figures 10 & 11

This derives mainly from the fact, that the integrated model assumed a perfect forecasting performance for the UC model. Although this can actually happen by traders in daily operations, as the UC model enables the actual representation of the real solution in the Greek day-ahead market, we provided a sensitivity analysis on the forecasting error of the UC model. Figure 12, provide the actual revenue margin, for the strategy with risk provisions, when the actual forecasting error of the UC model, deviates from the forecasting error of 0%, considered in the integrated model to decide the traded volumes. It derives that even for significant actual forecasting errors of the UC model, at the range of 20%, the risk strategy provides positive average revenue margins. Negative average revenue margins are estimated when the average forecasting error of the UC model exceeds 35%. The main reason behind this conclusion, is that the integrated model already considered high forecasting errors for the ANN models, which has led to conservative behaviour in the traded quantities. The consideration of “raw” data by the ANN model, by not excluding outliers in the historical training and test periods, has led to high forecasting errors on one hand but to enhanced risk performance on the other hand.

Insert Figure 12

To sum up, the traders have a risk of participating in the two markets, resulting from the uncertainty of several factors but as well the robustness of the price forecasting. The proposed integrated modelling approach provides insights on the trade-offs between price forecasts confidence, the adjustment factors, the accepted margins of the traders and the transmission rights. In total, it is a useful tool for the identification of the profitability of the traders, as well the eliminating the risk form the fluctuations of both markets.

5. Conclusions

This paper presents a model that integrates the Unit Commitment (UC) problem, which provides the power generation units’ dispatch and the electricity price forecasting of a power system with hybrid artificial neural network (ANN) models that incorporate a clustering algorithm, towards electricity price forecasting of a neighbouring power system. The integrated model is further extended to estimate the traders' profitability and risk, incorporating risk provisions.

The paper contributes to the literature examining the risk of traders from the participation in the cross-border electricity trade, resulting from the uncertainty of price forecasting. The applicability of the model concerns all physically interconnected power markets that are not market coupled, through a common market algorithm. The traders participate in explicit transmission rights' auctions and day-ahead markets, aiming at increasing their profitability. The integrated model is applied in bi-directional trading between the Italian and Greek day-ahead electricity markets. The UC model provides a robust forecast of the wholesale electricity price in Greece, while the ANN models cluster the data in homogenous groups, towards identifying periods with increased certainty on the Italian wholesale electricity price forecasting. The implementation of clustering techniques aims at identifying the time periods with high certainty of forecasting. The integrated model identifies periods with high price margins for trading for each power flow, aligned with a forecasting confidence and a risk level. Such cases are strongly related to the cases where transmission rights' prices have negligible values.

The confidence level of price forecasting, is estimated considering the historical price forecasting errors for each cluster. Based on the confidence level of the price forecasts, the trader adjusts its strategy both in the assumed prices but also the traded volumes. The paper examines how the incorporation of risk provisions, affects trader's profitability and the volumes traded. There are time periods, that a more aggressive trading approach, namely without risk strategy, could lead to higher margin for trade in one of the two directions. However, the overall performance of the trader for each direction, is more profitable when the trader incorporates the risk provisions. Moreover, the incorporation of risk provisions creates higher flexibility in trading, compared to the actual trading, as depicted in the results of the daily auctions of transmission rights, which show that traders are usually interested for trading only in one direction. The proposed integrated modelling approach provides insights on the trade-offs between price forecasts confidence, the adjustment factors, the accepted margins of the traders and the transmission rights' prices. The results of the model show that the consideration of risk provisions, based on "raw" data which include outliers, enhance risk performance and eliminate the risk for negative revenue margins. In total, it is a useful tool for the identification of the profitability of the traders, as well the eliminating the risk form the fluctuations of both markets.

The main contribution of this work is to provide a novel methodological framework which could reduce traders' risk, enhance the decision-making of energy traders in day-ahead energy markets, as well as help policy makers in the design of future energy markets.

Acknowledgement

The authors are grateful to the financial support of the Public Power Corporation S.A., through the research program B755/2016 of the Research Centre of the University of Piraeus, entitled "Risk management of the Public Power Corporation S.A.".

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Acronyms

ADMIE:	Independent Power Transmission System Operator
LAGIE	Hellenic Electricity Market Operator
GAMS:	General Algebraic Modelling System
MILP:	Mixed Integer Linear Programming
RAE	Regulatory Authority of Energy
RES:	Renewable Energy Sources
SMP:	System Marginal Price
UCP:	Unit Commitment Problem
PUN	National Single Price in the Italian Power Exchange
IPX	Italian Power Exchange
GME	Gestore dei Mercati Energetici S.p.A, the Italian Power Exchange
SUD	Southern Italy zone
TERNA	Italian Transmission System Operator S.p.A.
ANN	Artificial Neural Network

Nomenclature

Sets

$s \in S$	set of subsystems
$t \in T$	set of hours

$b \in B$	set of blocks of the energy offer function (bids) of each hydrothermal unit
$e \in E^z$	set of pumped storage units $e \in E$ interconnected with zone $z \in Z$
$g \in G^{hth}$	set of hydrothermal units
$g \in G^z$	set of units $g \in G$ that are (or can be) installed in zone $z \in Z$
$z \in Z$	set of zones
$n \in N^z$	set of interconnected power systems $n \in N$ with zone $z \in Z$
$n \in N$	set of interconnected power systems
$r \in R$	set of traders
$c \in C$	set of clusters, where time periods $t \in T$ are organized
$m \in M$	set of models for day-ahead price forecasting

Parameters

$CB_{g,b,t}$	Marginal cost of block $b \in B$ of the energy offer function of each unit $g \in G^{hth}$ in hour $t \in T$ (€/MW)
$CEP_{n,b,t}$	Marginal export bid of block $b \in B$ to interconnection $n \in N$ in hour $t \in T$ (€/MW)
$CIP_{n,b,t}$	Marginal cost of block $b \in B$ of the imported energy offer function from interconnection $n \in N$, in hour $t \in T$ (€/MW)
$CPM_{e,b,t}$	Marginal bid of block $b \in B$ of pumped storage unit $h \in H$ in

	hour $t \in T$ (€/MW)
$L_{z,t}$	Injection losses coefficient in zone $z \in Z$ and hour $t \in T$ (p.u.)
P_g^{min}	Technical minimum of each unit $g \in G^{hth}$ (MW)
P_g^{max}	Maximum power output of each unit $g \in G^{hth}$ (MW)
$RC1_{g,t}$	Price of the primary energy offer of each unit $g \in G^{hth}$, in hour $t \in T$ (€/MW)
$RC2_{g,t}$	Price of the secondary range energy offer of each unit $g \in G^{hth}$, in hour $t \in T$ (€/MW)
SDC_g	Shut-down cost of each unit $g \in G^{hth}$ (€)
$CAP_{s,t}$	Maximum allowed price for priced energy offers in subsystem $s \in S$ and hour $t \in T$
$MARG\_TOL_{r,t}$	Margin that satisfies the trader $r \in R$ to participate in cross-border trade in hour $t \in T$
$SMP_{s,t}$	System Marginal Price in subsystem $s \in S$ and hour $t \in T$ (Euro/MWh)
$SMP_{n,t}$	System Marginal Price in interconnected system $n \in N$ and hour $t \in T$ (Euro/MWh)
$TRA_{s,n,t}$	Transmission Right price, based on explicit Auction for the power flow from subsystem $s \in S$ to interconnected system $n \in N$ in hour $t \in T$ (Euro/MWh)

$TRA_{n,s,t}$ Transmission Right price, based on explicit Auction for the power flow from interconnected system $n \in N$ to subsystem $s \in S$ in hour $t \in T$ (Euro/MWh)

$TRQ_{s,n,r,t}$ Quantity traded by trader $r \in R$ from subsystem $s \in S$ to interconnected system $n \in N$ in hour $t \in T$ (MWh)

$TRQ_{n,s,r,t}$ Quantity traded by trader $r \in R$ from interconnected system $n \in N$ to subsystem $s \in S$ in hour $t \in T$ (MWh)

Continuous Variables

$exb_{n,b,t}$ Cleared quantity of power capacity block $b \in B$ exported to interconnected system $n \in N$ in hour $t \in T$ (MW)

$imb_{n,b,t}$ Cleared quantity of power capacity block $b \in B$ imported from interconnected system $n \in N$ in hour $t \in T$ (MW)

$pb_{g,b,t}$ Quantity of power capacity block $b \in B$ of unit $g \in G^{hth}$, dispatched in hour $t \in T$ (MW)

$pmb_{e,b,t}^{pum}$ Cleared quantity of block $b \in B$ of pumping unit $h \in H$ in hour $t \in T$ (MW)

$r1,_{g,t}^{up}$ Contribution of unit $g \in G^{hth}$ in primary-up reserve in hour $t \in T$ (MW)

$r2_{g,t}^{down}$ Contribution of unit $g \in G^{hth}$ in secondary-down reserve in hour $t \in T$ (MW)

$r2_{g,t}^{up}$ Contribution of unit $g \in G^{hth}$ in secondary-up reserve in hour

	$t \in T$ (MW)
$MARGIN_{s,n,t}$	Margin from cross-border trade between subsystem $s \in S$ and interconnected system $n \in N$ in hour $t \in T$
$MARGIN_{n,s,t}$	Margin from cross-border trade between interconnected system $n \in N$ and subsystem $s \in S$ in hour $t \in T$
$SMPF_{s,m,c,t}$	System Marginal Price Forecast in subsystem $s \in S$ and hour $t \in T$, for model $m \in M$ and cluster $c \in C$ (Euro/MWh)
$SMPF_{n,m,c,t}$	System Marginal Price Forecast in interconnected system $n \in N$ and hour $t \in T$, for model $m \in M$ and cluster $c \in C$ (Euro/MWh)
$SMPF'_{s,m,c,t}$	System Marginal Price Forecast in subsystem $s \in S$ and hour $t \in T$, for model $m \in M$ and cluster $c \in C$, updated by a price adjustment factor based on the confidence level of price forecasts (Euro/MWh)
$SMPF'_{n,m,c,t}$	System Marginal Price Forecast in interconnected system $n \in N$ and hour $t \in T$, for model $m \in M$ and cluster $c \in C$, updated by a price adjustment factor based on the confidence level of price forecasts (Euro/MWh)
$CONF_{s,m,c,t}$	Confidence level for price forecasting in subsystem $s \in S$ and hour $t \in T$, for model $m \in M$ and cluster $c \in C$ (%)
$CONF_{n,m,c,t}$	Confidence level for price forecasting in interconnected system $n \in N$ and hour $t \in T$, for model $m \in M$ and cluster

	$c \in C$ (%)
$ERRF_{s,m,c,t}$	Error of price forecasting for model $m \in M$, cluster $c \in C$ in subsystem $s \in S$ and hour $t \in T$ (%)
$ERRF_{n,m,c,t}$	Error of price forecasting for model $m \in M$, cluster $c \in C$ in system $n \in N$ and hour $t \in T$ (%)
$PADJ_{s,t}$	Price Adjustment factor in subsystem $s \in S$ and hour $t \in T$, based in the confidence level for price forecasting (%)
$PADJ_{n,t}$	Price Adjustment factor in interconnected system $n \in N$ and hour $t \in T$, based in the confidence level for price forecasting (%)
$QADJ_{s,n,t}$	Quantity Adjustment factor for trade from subsystem $s \in S$ to interconnected system $n \in N$ in hour $t \in T$, based in the confidence level for price forecasting (%)
$QADJ_{n,s,t}$	Quantity Adjustment factor for trade from interconnected system $n \in N$ to subsystem $s \in S$ in hour $t \in T$, based in the confidence level for price forecasting (%)
$TRQ'_{s,n,r,t}$	Quantity traded by trader $r \in R$ from subsystem $s \in S$ to interconnected system $n \in N$ in hour $t \in T$, updated by a quantity adjustment factor based on the confidence level of price forecasts (MWh)
$TRQ'_{n,s,r,t}$	Quantity traded by trader $r \in R$ from interconnected system $n \in N$ to subsystem $s \in S$ in hour $t \in T$, updated by a

	quantity adjustment factor based on the confidence level of price forecasts (MWh)
$REVENUE_{s,n,r,t}$	Profitability for trader $r \in R$ for participating in cross-border trade from subsystem $s \in S$ to interconnected system $n \in N$ in hour $t \in T$
$REVENUE_{n,s,r,t}$	Profitability for trader $r \in R$ for participating in cross-border trade from interconnected system $n \in N$ to subsystem $s \in S$ in hour $t \in T$
$REVENUE'_{s,n,r,t}$	Profitability for trader $r \in R$ for participating in cross-border trade from subsystem $s \in S$ to interconnected system $n \in N$ in hour $t \in T$, updated by risk management provisions
$REVENUE'_{n,s,r,t}$	Profitability for trader $r \in R$ for participating in cross-border trade from interconnected system $n \in N$ to subsystem $s \in S$ in hour $t \in T$, updated by risk management provisions
$REV\_MARG'_{s,n,r,t}$	Actual revenue margin for trader $r \in R$ for participating in cross-border trade from subsystem $s \in S$ to interconnected system $n \in N$ in hour $t \in T$, implementing risk management provisions
$REV\_MARG'_{n,s,r,t}$	Actual revenue margin for trader $r \in R$ for participating in cross-border trade from interconnected system $n \in N$ to subsystem $s \in S$ in hour $t \in T$, implementing risk management provisions

$REVENUE_{r,t}$	Profitability for trader $r \in R$ for participating in cross-border trade in hour $t \in T$
$REVENUE'_{r,t}$	Profitability for trader $r \in R$ for participating in cross-border trade in hour $t \in T$, updated by risk management provisions
$REV\_MARG'_{r,t}$	Actual revenue margin for trader $r \in R$ for participating in cross-border trade in hour $t \in T$, implementing risk management provisions
$REV\_MARG_{r,t}$	Actual revenue margin for trader $r \in R$ for participating in cross-border trade in hour $t \in T$ with no risk management provisions
$RISK\_PERF_{r,t}$	Performance of the risk management strategy for the trader $r \in R$ for participating in cross-border trade in hour $t \in T$
$QUANTITY_{r,t}$	Quantity traded by trader $r \in R$ in cross-border trade in hour $t \in T$
$QUANTITY'_{r,t}$	Quantity traded by trader $r \in R$ in cross-border trade in hour $t \in T$, updated by risk management provisions
$QUAN\_PERF_{r,t}$	Performance of the risk management strategy for the trader $r \in R$ in the quantities traded in cross-border trade in hour $t \in T$

Binary Variables

$x_{g,t}^{sd}$	1, if unit $g \in G^{hth}$ is shut-down in hour $t \in T$

$FLAG_{s,n,r,t}$ Flag for activating participation of trader $r \in R$ in cross-border trade from subsystem $s \in S$ to interconnected system $n \in N$ in hour $t \in T$,

$FLAG_{n,s,r,t}$ Flag for activating participation of trader $r \in R$ in cross-border trade from interconnected system $n \in N$ to subsystem $s \in S$ in hour $t \in T$,

Tables

1. Decomposition of the clusters of the selected ANN model for the examined period
2. The confidence level (CONF) of the day-ahead price forecasts, lead to adjustments of the price forecasts and the quantities to be traded, through adjustment factors for Price (PADJ) and Quantity (QADJ) respectively.
3. Average price (in €/MWh) forecasting errors, for a 24h time period, for each cluster of the ANN model.
4. Average hourly forecasted prices (in €/MWh) for the Greek and Italian SUD market (SMP_GR and SMP_IT respectively), average hourly prices of the transmission rights in both directions between the Greek and Italian SUD zones (TRA_IT_GR and TRA_GR_IT), hourly margin (in €/MWh) that satisfies the trader (MARG_TOL) and average hourly quantities (in MWh) traded in both directions (for the scenario where no risk strategy is implemented) (TRQ_imp and TRQ_exp respectively).

Table 1: Decomposition of clusters of the selected ANN model for the examined period

Cluster	Days of July 2016	Share (%)
1	4, 7, 8, 11, 15, 22, 28 and 29	25.81%
2	1, 5, 6, 12, 13, 14, 19, 20, 21, 26 and 27	35.48%
3	2, 9, 16, 18, 23, 25, 30 and 31	25.81%
4	3, 10, 17 and 24	12.90%

Table 2: The confidence level (CONF) of the day-ahead price forecasts, lead to adjustments of the price forecasts and the quantities to be traded, through adjustment factors for Price (PADJ) and Quantity (QADJ) respectively.

CONF		PADJ	QADJ
≥95%	100% or 1/100%	100%	100%
≥85%	95% or 1/95%	95%	85%
≥70%	85% or 1/85%	85%	70%
≥0%	70% or 1/70%	70%	35%

Table 3: Average price forecasting errors (in %), for a 24h time period, for each cluster of the ANN model.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Cluster1	12.2	10.7	11.7	12.5	11.3	11.6	11.6	11.6	12.2	13.0	9.9	11.6	9.8	11.3	9.9	9.0	8.8	10.6	11.4	11.3	9.7	7.8	8.8	10.3
Cluster2	8.8	7.7	8.4	9.5	9.8	10.0	7.7	6.5	8.7	11.3	11.0	12.9	14.9	19.1	71.9	12.1	11.9	7.9	9.3	9.4	8.4	7.6	6.5	6.9
Cluster3	14.1	19.2	20.5	27.4	28.5	34.3	24.9	24.2	32.4	99.4	89.2	88.3	31.1	80.2	116.7	29.3	19.6	16.6	17.2	15.3	20.8	15.2	14.2	15.5
Cluster4	16.8	14.8	15.3	19.1	24.5	18.5	20.1	35.6	40.0	50.2	22.8	32.8	29.3	91.4	53.7	161.9	50.6	44.7	31.9	36.3	36.9	30.5	26.0	17.7

Table 4: Average hourly forecasted prices (in €/MWh) for the Greek and Italian SUD market (SMP_GR and SMP_IT respectively), average hourly prices of the transmission rights in both directions between the Greek and Italian SUD zones (TRA_IT_GR and TRA_GR_IT), hourly margin (in €/MWh) that satisfies the trader (MARG_TOL) and average hourly quantities (in MWh) traded in both directions (for the scenario where no risk strategy is implemented) (TRQ_imp and TRQ_exp respectively).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
SMP_GR	43.17	42.98	41.68	41.00	40.06	39.40	40.47	42.41	42.21	42.69	42.56	42.80	43.27	42.42	42.51	42.77	43.05	43.14	43.31	43.28	45.08	43.87	43.70	44.45
SMP_IT	42.57	40.02	37.08	36.08	35.35	35.35	36.83	40.33	43.26	42.00	40.50	39.78	38.23	36.71	36.53	37.44	40.06	41.21	44.62	46.73	48.98	50.80	46.66	42.49
TRA_IT_GR	1.60	2.77	3.79	3.68	3.61	3.04	2.67	1.80	1.38	2.11	2.88	3.53	4.74	5.34	5.38	4.87	3.32	2.15	0.69	0.19	0.16	0.13	0.44	1.22
TRA_GR_IT	0.68	0.20	0.06	0.03	0.03	0.04	0.04	0.37	1.40	1.16	0.60	0.35	0.05	0.03	0.06	0.08	0.38	0.60	2.20	3.55	4.67	5.67	2.78	0.49
TRQ_imp	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
TRQ_exp	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
MARG_TOL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figures

1. Energy Supply offer for a thermal unit u, compared to its incremental cost and its minimum variable cost, for different power outputs, among unit's technical minimum P_u^{min} and technical maximum P_u^{max}. (Euro/MWh)

2. Determination of System Marginal Price (SMP), as the crossroad of aggregate Supply and Demand curves (Euro/MWh)

3. The configuration of the applied ANN model.

4. Typical System Marginal Prices in Italy (SMP_IT) and Greece (SMP_GR), as well as the Transmission Rights prices from the daily auctions for trade from Italy to Greece (TRA_IT_GR) and vice versa (TRA_GR_IT) in Euro/MWh

5. Average trader's profitability with risk provisions (REVENUE΄IT,GR, REVENUE΄GR,IT) compared to this without risk provisions (REVENUEIT,GR, REVENUEGR,IT), per each direction in trade among Italy & Greece (Euro)

6. Average quantity traded with risk provisions (QUANTITY΄IT,GR, QUANTITY΄GR,IT) compared to this without risk provisions (QUANTITYIT,GR, QUANTITYGR,IT), per each direction in trade among Italy & Greece (Euro)

7. Average trader's overall profitability with risk provisions (REVENUE΄IT,GR, REVENUE΄GR,IT) compared to this without risk provisions (REVENUEIT,GR, REVENUEGR,IT) for cross-border trade among Italy & Greece (Euro)

8. Risk performance indicator evolution per direction of trading (RISK_PERFIT,GR, RISK_PERFGR,IT) and in total (RISK_PERF), for cross-border trade among Italy & Greece, when risk provisions are considered (%)

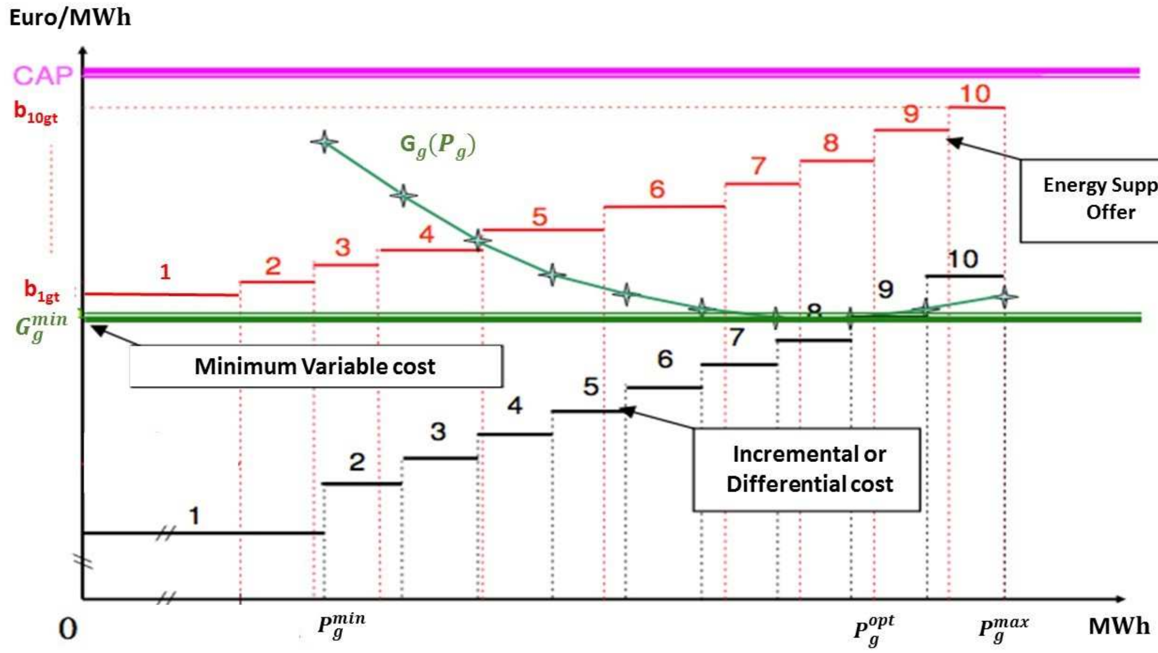
9. Evolution of the quantity performance indicator per direction of trading (QUAN_PERFIT,GR, QUAN_PERFGR,IT) and in total (QUAN_PERF), for

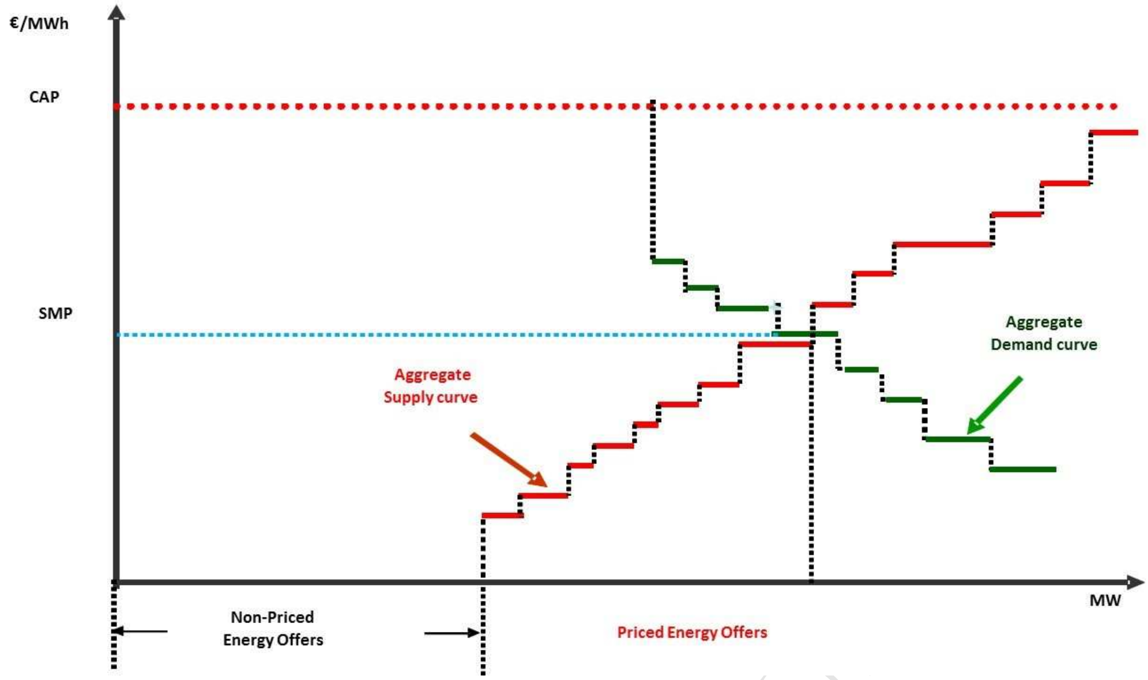
cross-border trade among Italy & Greece, when risk provisions are considered (%)

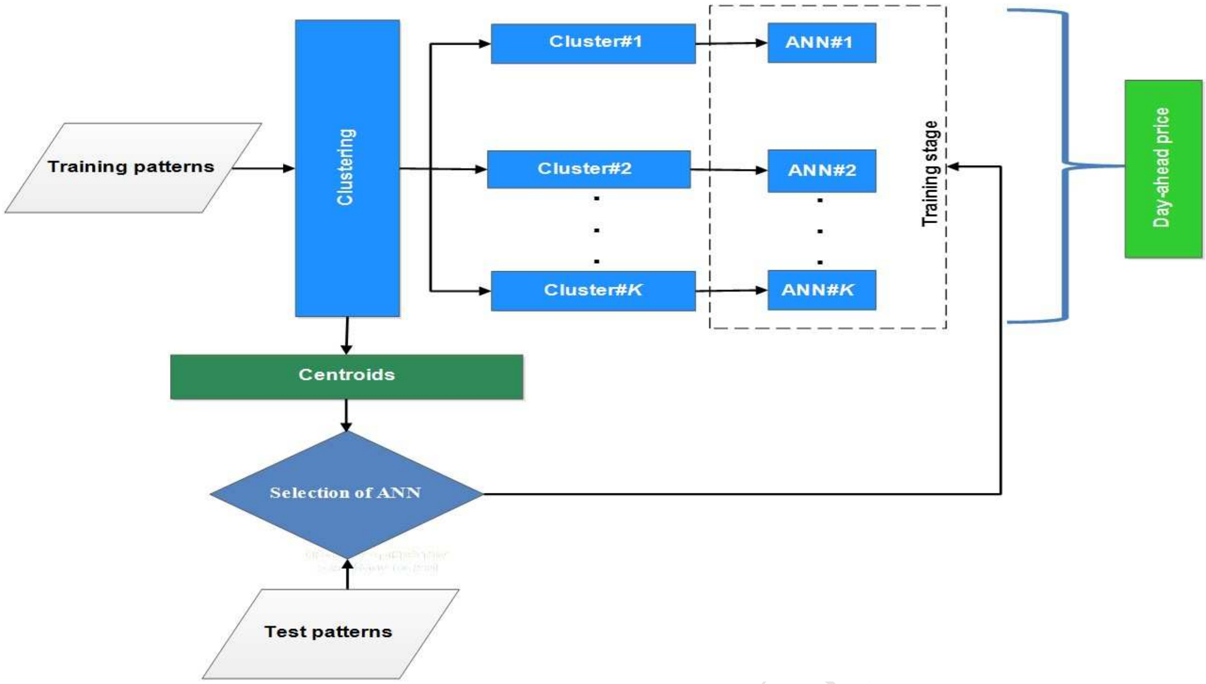
10. Average trader's revenue margin with risk provisions (REV_MARG΄IT,GR, REV_MARG΄GR,IT) compared to this without risk provisions (REV_MARGIT,GR, REV_MARGGR,IT), per direction of trade, for cross-border trade among Italy & Greece (Euro/MWh)

11. Average trader's revenue margin with risk provisions (REV_MARG΄) compared to this without risk provisions (REV_MARG) for cross-border trade among Italy & Greece (Euro/MWh)

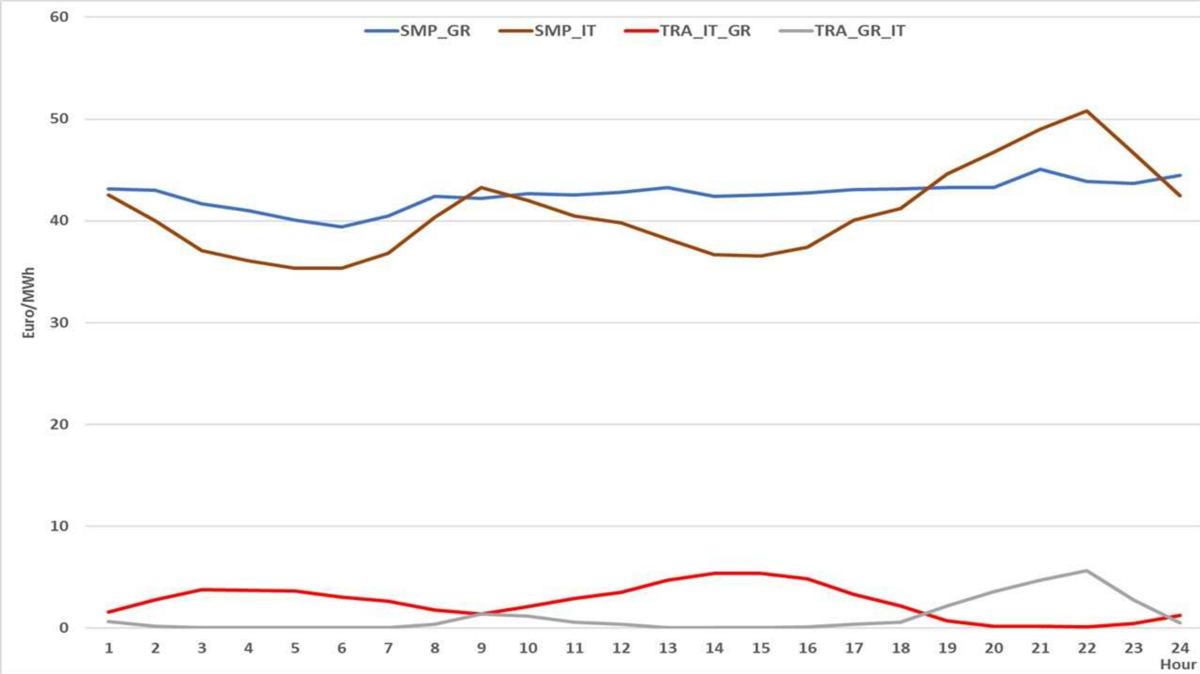
12. Average trader's revenue margin with risk provisions (REV_MARG΄), per different forecasting error of the Unit Commitment model, for cross-border trade among Italy & Greece (Euro/MWh)

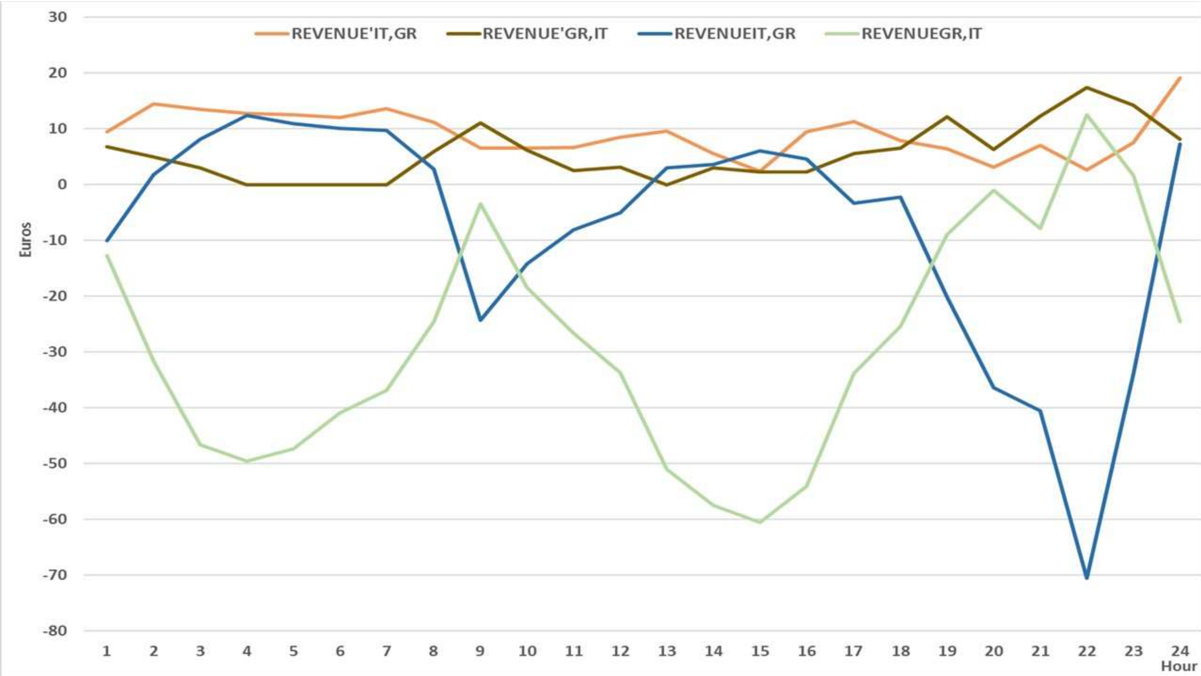

Euro/MWh
CAP
b_{10gt}
b_{1gt}
G_g^{min}
$G_g(P_g)$
Energy Supply Offer
Minimum Variable cost
Incremental or Differential cost
1
2
3
4
5
6
7
8
9
10
0
P_g^{min}
P_g^{opt}
P_g^{max}
MWh


€/MWh
CAP
SMP
Aggregate
Supply curve
Aggregate
Demand curve
MW
Non-Priced
Energy Offers
Priced Energy Offers

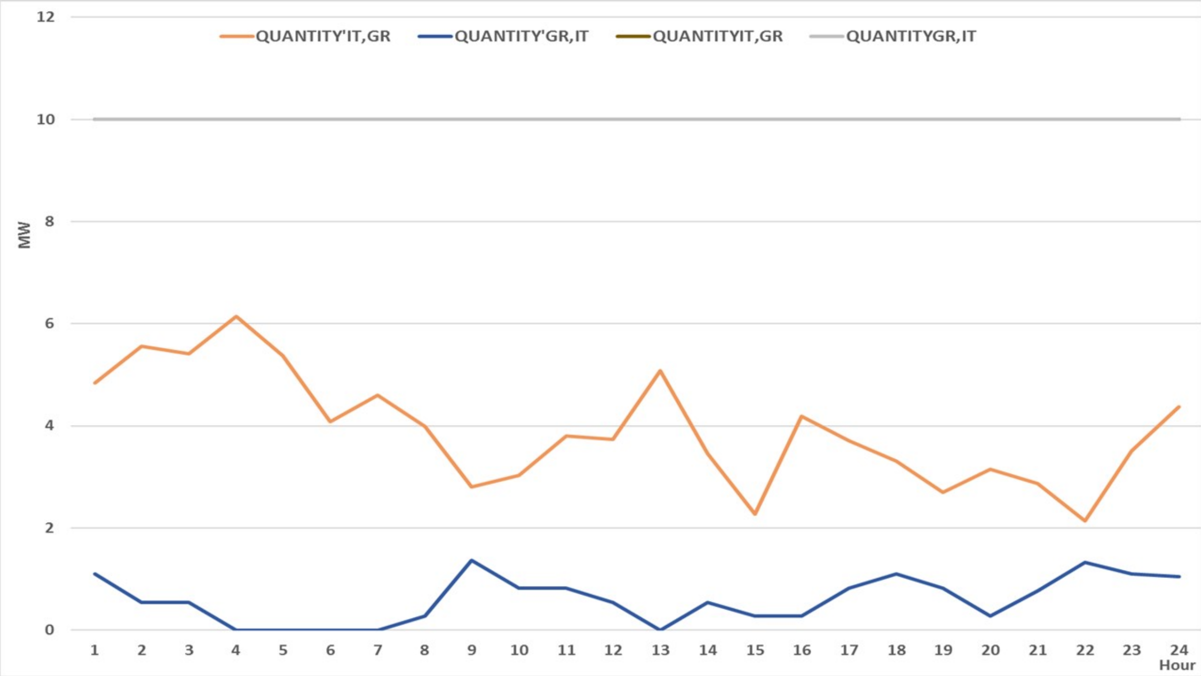


Training patterns
Clustering
Cluster#1
Cluster#2
Cluster#K
ANN#1
ANN#2
ANN#K
Training stage
Day-ahead price
Centroids
Selection of ANN
Test patterns

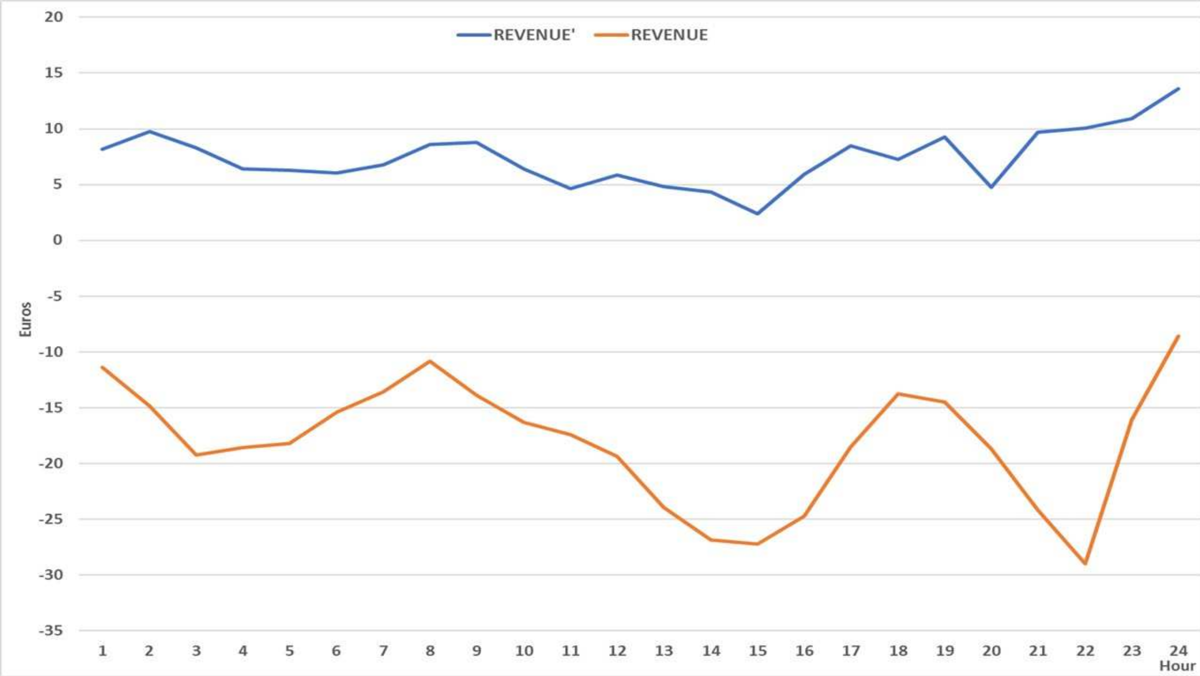

SMP_GR
SMP_IT
TRA_IT_GR
TRA_GR_IT
Euro/MWh
60
50
40
30
20
10
0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour



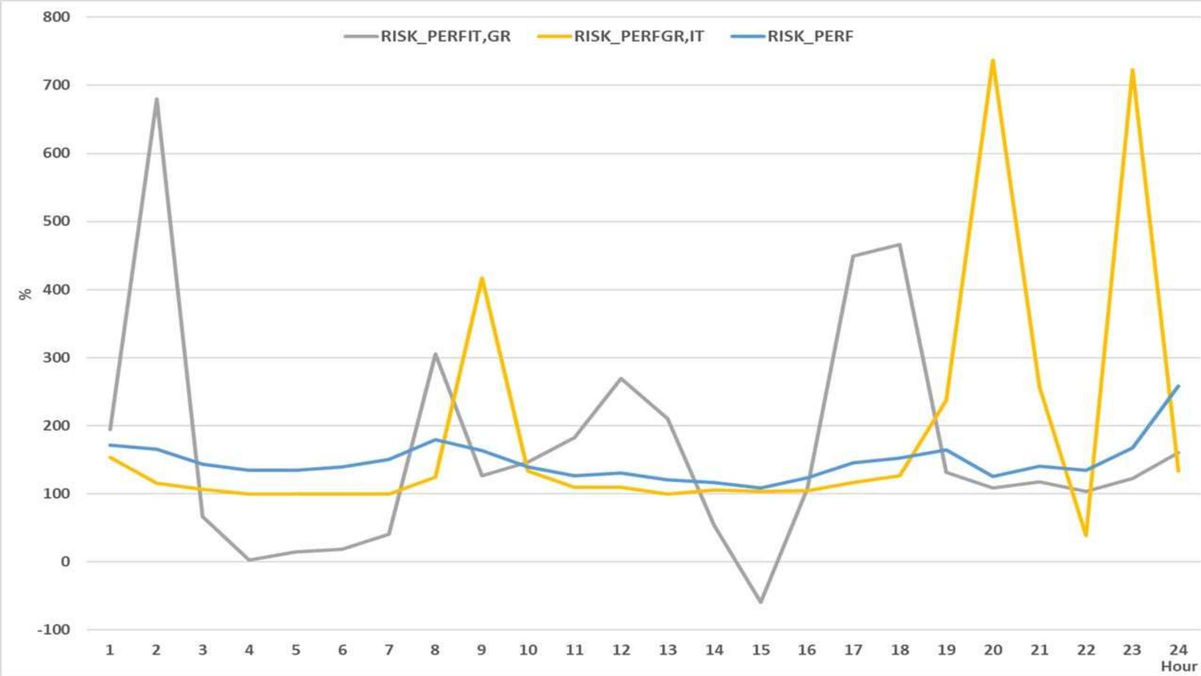
REVENUE'IT,GR
REVENUE'GR,IT
REVENUEIT,GR
REVENUEGR,IT
Euros
30
20
10
0
-10
-20
-30
-40
-50
-60
-70
-80
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour



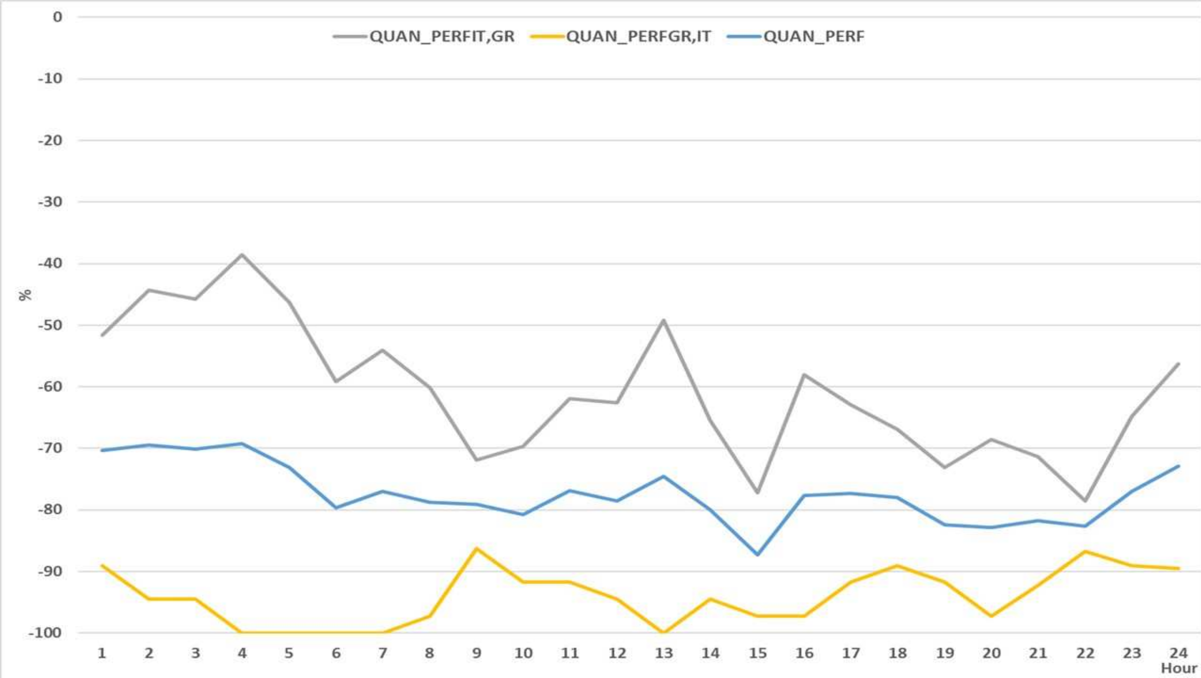
QUANTITY'IT,GR
QUANTITY'GR,IT
QUANTITYIT,GR
QUANTITYGR,IT
MW
Hour
0
2
4
6
8
10
12
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24



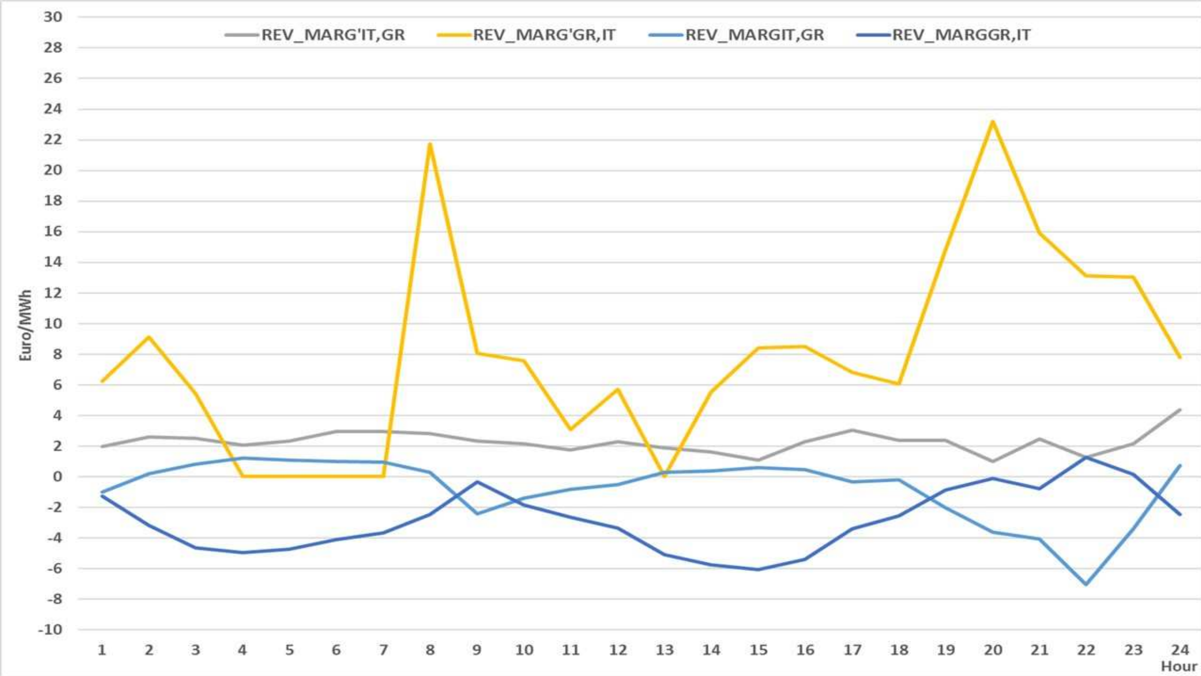
REVENUE'
REVENUE
Euros
Hour
20
15
10
5
0
-5
-10
-15
-20
-25
-30
-35
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24

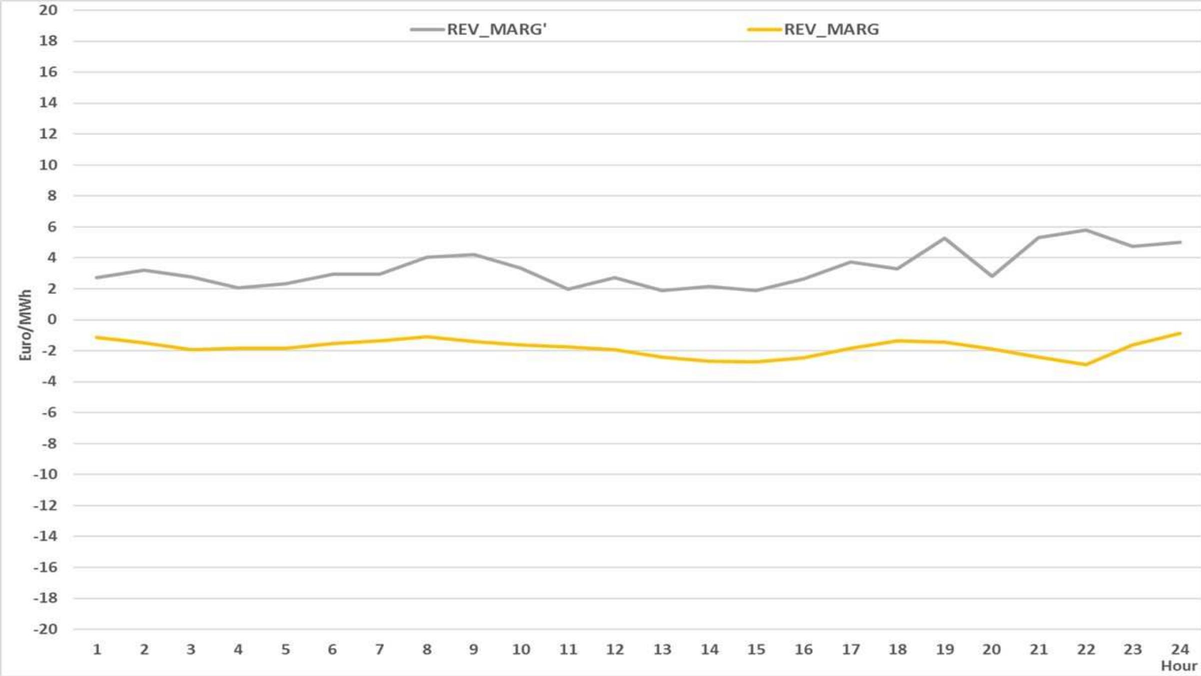


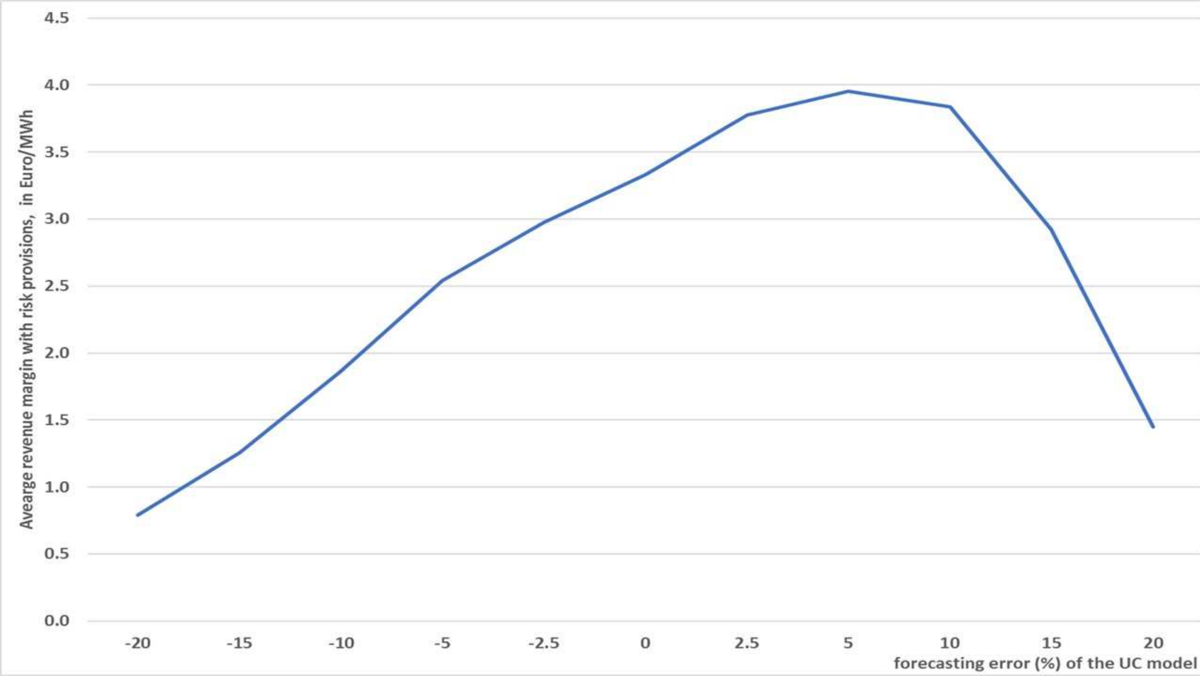
RISK_PERFIT,GR
RISK_PERFGR,IT
RISK_PERF
%
800
700
600
500
400
300
200
100
0
-100
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour



QUAN_PERFIT,GR
QUAN_PERFGR,IT
QUAN_PERF
%
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
-100
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Hour


REV_MARG'IT,GR
REV_MARG'GR,IT
REV_MARGIT,GR
REV_MARGGR,IT
Euro/MWh
Hour
30 28 26 24 22 20 18 16 14 12 10 8 6 4 2 0 -2 -4 -6 -8 -10
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24


REV_MARG'
REV_MARG
Euro/MWh
Hour
20
18
16
14
12
10
8
6
4
2
0
-2
-4
-6
-8
-10
-12
-14
-16
-18
-20
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24



Average revenue margin with risk provisions, in Euro/MWh
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
-20
-15
-10
-5
-2.5
0
2.5
5
10
15
20
forecasting error (%) of the UC model

Highlights

- integration of Unit-Commitment problem with ANN based models,
- clustering of the data to identifying periods with increased certainty on the day-ahead electricity price forecasting
- identification of periods with high price margins for electricity trade
- provision of price signals on the profitability of traders and
- provision of useful insights into the risk of traders