Comparison of Machine Learning Models for the Prediction of System Marginal Price of Greek Energy Market

Ioannis P. Panapakidis, Marios N. Moschakis

Abstract**—**The Greek Energy Market is structured as a mandatory pool where the producers make their bid offers in day-ahead basis. The System Operator solves an optimization routine aiming at the minimization of the cost of produced electricity. The solution of the optimization problem leads to the calculation of the System Marginal Price (SMP). Accurate forecasts of the SMP can lead to increased profits and more efficient portfolio management from the producer`s perspective. Aim of this study is to provide a comparative analysis of various machine learning models such as artificial neural networks and neuro-fuzzy models for the prediction of the SMP of the Greek market. Machine learning algorithms are favored in predictions problems since they can capture and simulate the volatilities of complex time series.

Keywords**—**Deregulated energy market, forecasting, machine learning, system marginal price, energy efficiency and quality.

I. Introduction

ELECTRICITY market prices time series are characterized by high volatility [1]. This is due to several factors such as sudden demand increases, fuel prices such as coal, petroleum products and natural gas, operational characteristics of generation plants and merit order, hydropower capacity, market competition, market regulation, network congestion and others [2]. This dependence by many and diverse factors provide obstacles in price forecasting.

Contrary to demand forecasting, electricity price forecasting has gathered less research interest [3]. Until the recent years, most markets were structures as monopolies and prices were subject to regulative determination and control. While more and more markets have been transforming to competitive, price forecasting is viewed as an important aspect in power system operation. It is related with unit scheduling, fuel consumption, energy resources exploitation, power systems simulation and electricity demand modeling.

Another fact that price forecasting holds a significant role is in profit maximization problems. Many studies had examined the retail profitability problem in competitive retail markets [35]-[40]. In this problem, the scope is two-fold: The retailer needs to define the optimal electricity procurement mechanism and the optimal selling price to its clients. The procurement mechanisms refer to pool market, forward contracts and others. If the retailer is risk taker and bases its procurement in pool market, a reliable price forecasting model is needed. If forecasting errors are high, the retailer will eventually led to economic failure. Regarding the selling price to the consumers, a price forecasting model is the basis to form real-time pricing schemes [4], [5]. Real-time pricing is viewed as the most accurate and fair pricing concept; it allows to transfer to the consumers the actual generation costs [6], [7].

The price forecasting literature can be classified into [8], [9]: a) Time-series models and b) computational intelligence models. In the time-series models, a mathematical function is built that connects the current price with its past values. The user needs to define the type and the parameter of the function. In computational intelligence model no information about the relationship between the parameter under study and its past values is mandatory. Through a training phase the model "learns" the relationship between input and output training patterns. This leads to the automatic creation of the function that relates the inputs and outputs.

The aforementioned scheme provides benefits in cases of time-series with high degree of non-linearity. Computational intelligence models include Artificial Neural Network (ANN), fuzzy logic, neuro-fuzzy models and others. The types of ANNs that have been examined in price forecasting literature are the Multi-Layered Perceptrons (MLPs), Radial Basis Function Networks (RBFNs), Support Vector Machines (SVMs), Fuzzy Neural Networks (FNNs), Recurrent Neural Networks (RNNs), Probabilistic Neural Networks (PNN) and Self-Organizing Maps (SOMs).

The MLPs are implemented as the sole forecaster in [10]-[18] or in hybrid models utilizing MLP and another forecasting system [19]-[21]. Within a hybrid model, the MLP is used to increase the accuracy of a traditional time-series models. Other papers consider the same MLP for both demand and price predictions [22], [23]. It should be noted that MLP has been used both for day-ahead and hour-ahead predictions [24].

SVMs are systems that implement a non-linear mapping of the original data into high dimensional space [25], [26]. SVMs provide a global solution to the forecasting problem contrary to MLPs that can be trapped in local minima during the training phase. The SVM is used for calculating the prediction intervals which quantify the uncertainty related to forecasts [27].

SOMs are unsupervised machine learning neural networks that are mainly used in clustering tasks. In [28] the SOM is

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combined with a SVM for the price forecasting in New England market and in [29] they are combined and used for the PJM market.

Fuzzy logic can be combined with ANN forming neuro-fuzzy systems. The most common neuro-fuzzy model is the Adaptive Neuro-Fuzzy Inference System (ANFIS). This model operates well by using past prices that are very close chronologically with the one to be predicted. In [30], the ANFIS is combined with FL and ANN for price forecasting in Spain.

The scope of the present paper is to examine the potential of MLP and ANFIS in day-ahead price forecasting for the Greek energy market. The Greek market operates as pool where the producer provides their bids and retailer provide request for load coverage. The SMP is a product of an algorithmic optimization problem solution and is the price that all producers are credited and retailers are charged daily. The Market Operator (LAGIE SA) solves the optimization problem and oversees the market [31]. In the present paper, various combinations of FFNN are examined in order to fully investigate the performance of a "black-box" modeling, such as a FFNN, approach in the SMP forecasting problem. A comparison takes place between FFNN and ANFIS.

II. Models Description

A. Data

The data under study involve the SMP of the Greek interconnected system of the period 2010-2013. The period between 01/01/2010 and 31/12/2012 is used as training set and the period 01/01/2013 and 31/12/2013 as test set. The training set is used to define the optimal model parameters. For the FFNN, the parameters that need to be defined are: Training algorithm, number of hidden layers, number of neurons in the hidden layer(s) and type of neuron activation function. For ANFIS, the parameters are: Type of membership function and type of inference mechanism. The test set is used for the assessment of the models performance.

Fig. 1 presents the SMP time-series of 2013. It can be noticed that there are many fluctuations and zero values and thus, special care should be placed on the selection of types and number of inputs of the models. Note that no external variables are considered such as load, hydraulic capacity, temperature and others. The scope is to use as inputs only historical SMP values.

B. Input Selection

In order to explore the SMP series periodicity, the Pearson correlation coefficient is used to measure the degree of dependence between current values and values up to 9 days in the past [24]. The results are presented in Fig. 2. SMP series present a periodic correlation with previous values. However, the degree of correlation is relatively low. Let $P(h)$ be the SMP of the present hour h. Excluding $P(h\text{-}1)$ and $P(h\text{-}2)$ all other values are below 0.67. Since this study is focused on forecasting next day`s SMP curve, prices prior to $h$-24 are not used; they are considered unknown. For predicting the $P(h)$, prices $P(h\text{-}24)$, $P(h\text{-}25)$ and $P(h\text{-}168)$ are selected as inputs. The models are executed per hour, therefore for predicting next day` s SMP curve 24 executions are held, separately from each forecaster.

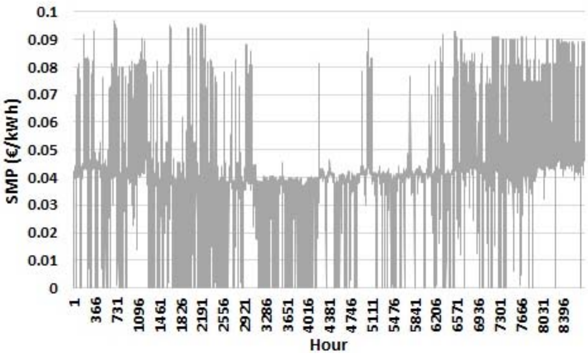

Fig. 1 SMP time-series of the test set

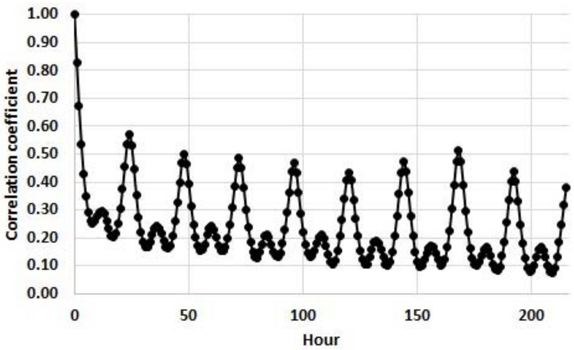

Fig. 2 Correlation coefficient values evaluating the short-term periodicity model

C. Models

The FFNN is popular computational intelligent model. FFNN displays the benefit of adaption to a problem`s requirements. Fig. 3 presents a general structure of a fully connected FFNN. The FFNN network is built by the neurons which are information processing units. The neuron is fed with a set of discrete signals that are modified by the weights of the synapse which generates an output based on the form of the activation function of the neurons [32]. While neural networks are "black-box" models, there is a set of parameters that need to be defined. These parameters determine the neural network`s structure. The training phase aims to optimize the weights that connect the neurons via a cost function iterative minimization process. Other parameters such as type of training algorithm, maximum number of training epochs, number of hidden layers and others, are determined by trial-and-error experiments.

ANFIS is composed by 5 layers and each layer contains several nodes [33]. The nodes are described by a node function. Fig. 4 presents the structure of ANFIS. This model is considered as universal approximator. The core of ANFIS is the inference system that refers to a set of fuzzy IF-THEN rules that are characterized by their learning capability to approximate nonlinear functions and signals.

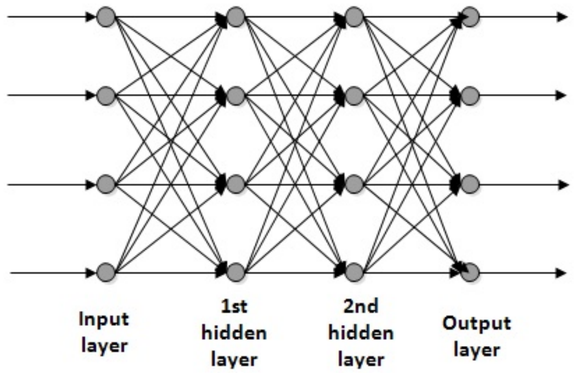

Fig. 3 General structure of FFNN

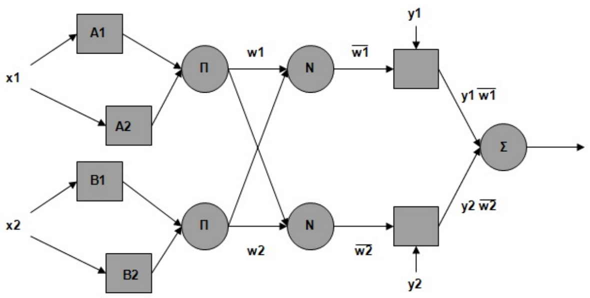

Fig. 4 General structure of ANFIS

D. Validation

Let P_m^{a} and P_m^{f} are the actual and predicted SMP of the *m*-th day of the test set. The Mean Absolute Range Normalized Error (MARNE) is the absolute difference between the actual and forecast SMP, normalized to the maximum SMP [34]:

$$\text{MARNE}=\frac{1}{M}\sum_{m=1}^{M}\frac{\left|P_m^{\text{a}}-P_m^{\text{f}}\right|}{\max(P_m^{\text{a}})}\times 100 \tag{1}$$

MARNE is percentage indicator that provides a reliable metric in cases of time-series with zero or close to zero values. The MAPE indicator is widely used in load forecasting studies [35]. However, for time series with close to zero values such as the SMP of the Greek market, MAPE receives extremely large values, a fact that makes it less practical to draw conclusions regarding the robustness of a model.

III. Results

For the FFNN, three different functions are considered, namely the logistic sigmoid (log.), the hyperbolic tangent sigmoid (tan.) and the linear (lin.) functions. Two training algorithms are considered namely the Levenberg–Marquardt (LM) and the Resilient Back-Propagation (RBP). These training algorithms are improvements of the basic back-propagation algorithm. For both FFNN and ANFIS the maximum number of epochs is set to 500. ANFIS parameters are Sugeno type inference mechanism and Gaussian membership function. While there is a gap in the literature for SMP forecasting in the Greek energy market, a detailed analysis is recommended to investigate various topologies of FFNNs. For the determination of the optimal topology, a series of experiments takes place that differ in terms of neuron activation function and training algorithm. One hidden is considered for FFNN and the number of neurons varies between 2 and 30 with an increasing step of 1.

Tables I-IV present the training set and test set errors for the different topologies of FFNN. The MARNE values refer to the lowest one that corresponds to the experiment with variable number if neurons in the hidden layer. According to the results presented in the tables, the lower MARNEs are obtained by the RBP training algorithm for both the training and test sets. For the LM algorithm, training set MARNE ranges from 7.76% to 18.16% while test set MARNE ranges from 10.22% to 36.07%. For the RBP algorithm, training set MARNE ranges from 7.10% to 18.11% while test set MARNE ranges from 9.46% to 36.10%. The use of logistic function in the output layer leads to errors above 30%, a fact that prohibits its usage and indicated model`s poor performance. The lowest error is 9.46% and refers to the network with logistic function in the hidden layer and tangent sigmoid in the output one.

TABLE I
Training Set Marne (LM Algorithm)

Hidden layer	Output layer		
	log.	**tan.**	**lin.**
log.	17.90	7.75	7.76
tan.	17.93	7.78	7.76
lin.	18.16	7.95	7.91

TABLE II
Test Set Marne (LM Algorithm)

Hidden layer	Output layer		
	log.	**tan.**	**lin.**
log.	36.07	10.22	10.25
tan.	36.06	10.24	10.42
lin.	36.11	10.28	10.53

TABLE III
Training Set Marne (RBP Algorithm)

Hidden layer	Output layer		
	log.	**tan.**	**lin.**
log.	17.87	7.12	7.14
tan.	17.89	7.10	7.23
lin.	18.11	7.37	7.39

TABLE V
Test Set Marne (RBP Algorithm)

Hidden layer	Output layer		
	log.	**tan.**	**lin.**
log.	36.06	9.57	9.46
tan.	36.08	9.54	9.60
lin.	36.10	10.08	10.40

The consideration of tangent function leads in general to robust performance. Figs. 5-8 present the MARNE curves with respect to the number of neurons in the hidden layer for various topologies. It can be noticed that the variation of the number of neurons do not considerable influence the prediction accuracy.

Regarding the application of ANFIS, the training set used for FFNN leads to the no convergence of the model. A reduction of the training set took place and more specifically, the training set used for ANFIS corresponds to the period 01/01/2012-31/12/2012. The training set MARNE is 7.42% and test set MARNE is 9.22%. In conclusion, for the SMP problem under study, ANFIS is superior to FFNN.

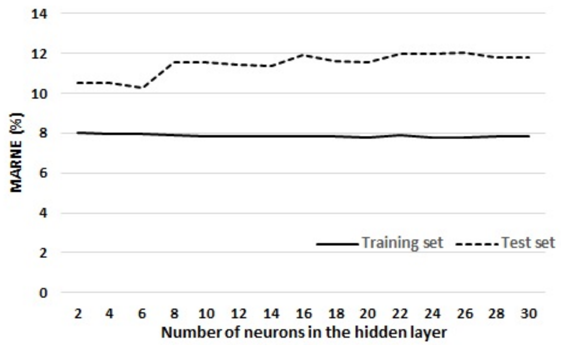

Fig. 5 MARNE variation per number of neurons in the hidden layer for FFNN trained by LM and using tangent sigmoid function for the hidden and output layer

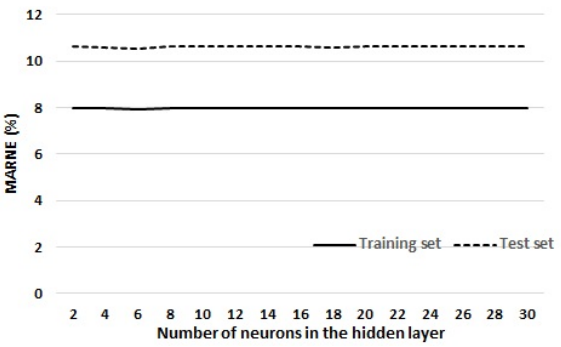

Fig. 6 MARNE variation per number of neurons in the hidden layer for FFNN trained by LM and using linear function for the hidden and output layer

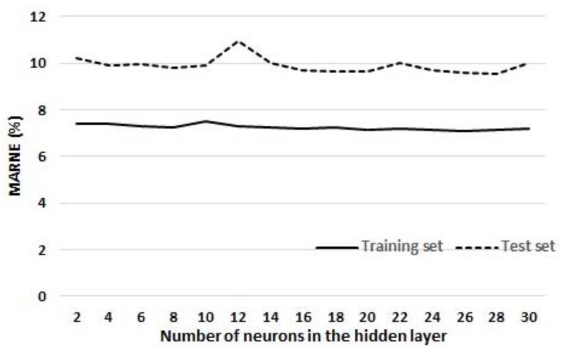

Fig. 7 MARNE variation per number of neurons in the hidden layer for FFNN trained by RBP and using tangent sigmoid function for the hidden and output layer

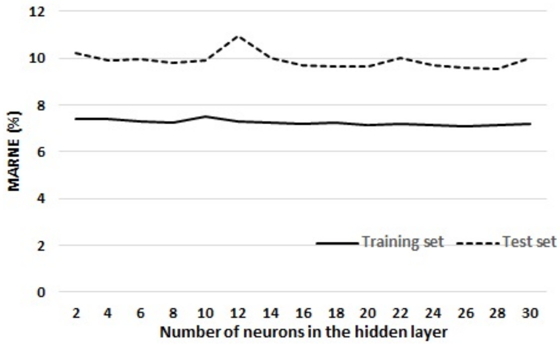

Fig. 8 MARNE variation per number of neurons in the hidden layer for FFNN trained by RBP and using linear function for the hidden and output layer

IV. Conclusions

With the continuous deregulation of energy markets across the globe, new opportunities arise for market participants. Market prices are the output of day-ahead strategic actions of the participants. The SMP is influenced by many factors such as demand, natural gas prices, renewable energy sources capacity and others. This leads to increased volatility in shape of the SMP time series. The aforementioned fact provides obstacles in the utilization of traditional time series models and hence, more advanced algorithms should be examined.

The aforementioned fact provides obstacles in the utilization of traditional time series models and hence, more advanced algorithms should be examined. The present paper serves as an initial step to examine the potential of computational intelligence models in SMP forecasting for the Greek energy market. While there is a lack in the literature for studies in SMP forecasting for the Greek sector, various combination of FFNN were investigated in order to fully check the relationship between network parameters and prediction accuracy. Simulation results indicate that the parameters of the FFNN influence the results. Among the two models, ANFIS leads to lower errors and therefore, it is more suitable for the problem under study.

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