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Greek long-term energy consumption prediction using artificial neural networks

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Abstract

In this paper artificial neural networks (ANN) are addressed in order the Greek long-term energy consumption to be predicted. The multilayer perceptron model (MLP) has been used for this purpose by testing several possible architectures in order to be selected the one with the best generalizing ability. Actual recorded input and output data that influence long-term energy consumption were used in the training, validation and testing process. The developed ANN model is used for the prediction of 2005-2008, 2010, 2012 and 2015 Greek energy consumption. The produced ANN results for years 2005-2008 were compared with the results produced by a linear regression method, a support vector machine method and with real energy consumption records showing a great accuracy. The proposed approach can be useful in the effective implementation of energy policies, since accurate predictions of energy consumption affect the capital investment, the environmental quality, the revenue analysis, the market research management, while conserve at the same time the supply security. Furthermore it constitutes an accurate tool for the Greek long-term energy consumption prediction problem, which up today has not been faced effectively.

Keywords: Artificial neural networks; energy consumption; gross domestic product; installed capacity; multilayer perceptron; prediction.

1. Introduction

Energy consumption has increased remarkably over the past decades all over world due to the increasing population and the economic development. Energy is considered as an important factor in the economic and social development of a country and consequently in the people's wealth. Long-term energy consumption predictions are essential and are required in the studies of capacity expansion, energy supply strategy, capital investment, revenue

analysis and market research management. However, the large number of uncertainties that characterize long-term predictions, which sometimes cover up to thirty years ahead, have as a result the unimpaired interest of scientists in this particular field and the continuous development of new approaches for more accurate and reliable predictions.

Artificial intelligence, including both genetic algorithms and artificial neural networks (ANN), was used in order to predict the electrical energy consumption in [1]. ANN models were also developed for the Turkey's net energy consumption prediction in [2]. A hybrid fuzzy neural technique, which combines neural network and fuzzy logic modeling, was used for long-term prediction in [3] producing accurate results. Multiple linear regression analysis models for long-term prediction have reported in [4], while such models have extensively used in several prediction problems, since they have presented very good results [5-8]. Long-term prediction approaches have been also developed based on the complete decomposition method [9] and univariate models such as: the autoregressive, the autoregressive integrated moving average and a novel configuration combining an autoregressive with a high pass filter were proposed in [10]. Significant was also the work presented in [11] where three different modeling techniques for the prediction of electricity energy consumption, i.e., regression analysis, decision tree and neural networks, were considered and comparative advantages of the different data analysis approaches were presented. Finally electricity load forecasting has been proposed using support vector regression models [12] and support vector machines with simulated annealing algorithms [13].

In the current work the Greek long-term energy consumption for the years ahead is predicted, exploiting ANN computational speed, ability to handle complex non-linear functions, robustness and great efficiency even in cases where full information for the studied problem is absent. The multilayer perceptron model (MLP) has been used for this purpose. Several possible architectures are tested and the one with the best generalizing ability is selected. Actual recorded input and output data that influence long-term energy consumption were used in the training, validation and testing process. The developed ANN model is used for the prediction of 2005-2008, 2010, 2012 and 2015 energy consumption producing very accurate results comparing them with the results of a linear regression method, a support vector machine method and the actual available recorded data for years 2005-2008.

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The proposed approach can be very useful in the effective implementation of energy policies since accurate predictions of energy consumption affect the capital investment, the environmental quality, the revenue analysis, the market research management, while conserve at the same time the supply security. Furthermore the proposed approach could be an accurate tool for the Greek long-term energy consumption prediction problem, which up today has not been faced effectively.

2. Artificial neural networks (ANN)

An artificial neural network consists of a number of very simple and highly interconnected processors, called neurons, which are analogous to the biological neurons in the brain. The neurons are connected by weighted links that pass signals from one neuron to another. Each link has a numerical weight associated with it. Weights are the basic means of long-term memory in ANN. They express the strength, or importance, of each neuron input. A neural network "learns" through repeated adjustments of these weights. The characteristic feature of these networks are that they consider the accumulated knowledge acquired during training and respond to new events in the most appropriate manner, giving the experience gained during the training process. In this work a typical neural network model known as multilayer perceptron model (MLP) has been used. The MLP is a feed forward neural network with an input layer of source neurons, at least one middle or hidden layer of computational neurons, and an output layer of computational neurons (Fig. 1). The input layer accepts input signals from the outside world and redistributes these signals to all neurons in the hidden layer. The hidden layer detects the feature. The weights of the neurons in the hidden layers represent the features in the input patterns. The output layer establishes the output pattern of the entire network [14].

In order to train the network, a suitable number of representative examples of the relevant phenomenon must be selected so that the network can learn the fundamental characteristics of the problem. More than a hundred different learning algorithms are available, but the most popular one is the backpropagation. In a backpropagation neural network the learning algorithm has two phases. First a training input data set is presented to the network input layer. The network then propagates the input data set from layer to layer until the output data set is generated by the output layer. If this data set is different from the desired output, an error is calculated and then propagated backwards through the network from the output layer to the input layer. The weights are modified as the error is propagated [14, 15].

ANN models are determined according to their architecture, i.e., the network's structure, transfer function and learning algorithm. In the backpropagation networks the MLP architecture is generally decided by trying a) varied combinations of number of hidden layers and number of nodes in a hidden layer, b) different transfer functions and c) learning algorithms in order to be selected the most suitable ANN model architecture, which has the best generalizing ability amongst the all tried combinations [15, 16], i.e., minimization of the sum-squared error. Once the training process is completed and the weights and bias of each neuron in the neural network is set, the next step is to check the results of training by seeing how the network performs in situations encountered in training and in others not previously encountered.

Although there are several different types of artificial neural networks in this study the backpropagation MLP model has been used. The main reasons were: a) small solution network and quick computational speed that permits training over large input data sets, b) automatic generalization of knowledge enabling the recognition of data sets, c) robustness to recognize data obscured by noise, d) minimization of the mean squared aggregate error across all training data sets and e) supervised training. The main disadvantage of the backpropagation MLP is the many variables which must be considered when constructing a MLP. This includes the number of hidden layers, the type of transfer function(s), the initial conditions, and the types of backpropagation MLPs available. One must also consider the training time which is a direct function of training set size and MLP chosen for the task.

3. Energy consumption

Energy forms a key part of humans' everyday lives. Energy is needed in almost every activity. As economy grows, demand for energy dramatically increases. According to the American Energy Information Administration (AEIA) and to the International Energy Agency (IEA), the world-wide energy consumption will on average continue to increase by 2.5 % per year and this forms a modest prediction.

In Greece the final energy consumption which includes all energy delivered to the final consumer's door (industry, transport, households and other sectors) for all energy uses, has increased the last 16 years more than 60 %, from 14,079,000 Tones of Oil Equivalent (TOE) in 1992 to 22,552,000 TOE in 2007 following an average annual increase of approximately 4.1 % [17]. Fig. 2 presents the Greek final energy consumption in comparison to the Greek gross domestic product (GDP) from 1992 to 2007, showing clearly the relation of economy and energy consumption [17].

Fig. 3 indicates similar findings. As it can be seen the Greek installed power capacity in MW and the Greek yearly per resident electricity consumption in kWh have increased significantly the last 16 years [18, 19]. Their continuous increase which is not expected to be stabilized or to be decreased would certainly have a great influence on the Greek long-term energy consumption. At this point it must be mentioned that the Greek installed capacity continues increases due to the rapid installation of renewable energy technologies which hold today (2008) only a 9 % of the total installed capacity with a goal of 20 % power installed capacity in year 2020.

A very crucial factor that also affects energy consumption is climate. The yearly ambient temperature increase has a considerable effect in the energy consumption for very obvious reasons, i.e., increase in temperature leads to a higher use of air conditioners and other cooling devices. Recent studies have concluded that the sensitivity of energy consumption to temperature has increased in the recent period [20, 21]. Given the concern about global warming, these findings support the renewed interest in energy related questions by the policymakers.

4. Design of the proposed MLP ANN model

The goal of this study is to develop an artificial neural network architecture capable to predict the Greek long-term energy consumption. The four parameters analyzed in the previous section, that play important role to the long-term energy consumption were selected as the inputs to the neural network, while as output the final energy consumption was considered. These parameters, summarized in table 1, constitute actual recorded data. More specifically, the yearly ambient temperature T has been supplied from the Greek National Meteorological Service [22], the installed power capacity C and the yearly per resident electricity consumption R have been supplied from Public Power Corporation S.A. [18, 19], while the gross domestic product G has been supplied from EUROSTAT [17]. Finally the output variable, i.e., the final energy consumption F has been also provided from EUROSTAT [17].

It must be mentioned that the author has selected only those four input parameters for the designed ANN model, although there are also others (e.g. amount of CO_2 pollution, number of air-conditioners, installation of renewable energy technologies, electricity price, etc.), that affect the energy consumption. The reason of this selection was that there were not available real records of data for any other parameters.

As it has stated earlier each ANN model is determined according to its structure, the transfer function and the learning algorithm, which are used in an effort to learn the network the fundamental characteristics of the examined problem. In this work, thousands MLP ANN models were designed and tested. These were combinations of five backpropagation learning algorithms, five transfer functions and structures consisted of 1 to 5 hidden layers with 2 to 100 neurons in each hidden layer (table 2).

The MATLAB® neural network toolbox [23, 24] was used to train the developed neural network models. Input and output data of the last 13 years (1992-2004), were used to train and validate the neural network models. In each training iteration 20 % of random samples were removed from the training set and validation error was calculated for these data. The training process was repeated until a root mean square error between the actual output and the desired output reached the goal of 1 % or a maximum number of epochs (the presentation of the set of training data to the network and the calculation of new weights and biases) it was set to 15,000, was accomplished. Finally, the predicted energy consumption value was checked with values obtained from situations encountered in the training and others which have not been encountered.

It must be mentioned that prior the ANN training, data normalization was performed. This was necessary not only because all entries need to be guaranteed to have the same weight, but also because the range of values must be limited for neurons' transfer function in order the network to converge in training and produce meaningful results [25]. Although several normalization methods exist, common feature of all these is that an offset is deducted from the data items, after which they are transformed over the desired range by means of a scaling factor. The most commonly employed method for normalization involves mapping the data linearly over a specified range, whereby each value of a variable x is transformed as follows:

$$x' = \frac{\left(x'_{max} - x'_{min}\right)}{x_{max} - x_{min}} \cdot \left(x - x_{min}\right) + x'_{min}$$

$$= \frac{\left(x'_{max} - x'_{min}\right)}{x_{max} - x_{min}} \cdot x + \left(x'_{min} - \frac{\left(x'_{max} - x'_{min}\right)}{x_{max} - x_{min}} \cdot x_{min}\right)$$

$$= factor \cdot x + offset \tag{1}$$

where x_{max} and x_{min} are the expected maximum and minimum values of the concerned variable. x'_{max} and

x'_{min} specify the desired values of the range for the transformed variable [26].

After extensive simulations with all possible combinations of the 5 backpropagation learning algorithms, the 5 transfer functions, the 1 to 5 hidden layers and the 2 to 100 neurons in each hidden layer, it was selected and used further to predict the Greek energy consumption the model that presented the best generalizing ability, had a compact structure, a fast training process and consumed lower memory. This MLP ANN model had the following characteristics: 2 hidden layers, with 20 and 17 neurons in each one of them, Levenberg-Marquardt backpropagation learning algorithm and logarithmic sigmoid transfer function. The mean square error was minimized to the final value of 0.010 within 13,318 epochs. Table 3 presents the training data of the best 10 designed ANN models which have presented the best generalizing ability among all the others designed.

5. Test results – Error Analysis

The selected ANN model has been used in order to predict the Greek long-term energy consumption. Predictions have been made for years 2005-2008, 2010, 2012 and 2015. Table 4 presents the results produced by the developed ANN model and the real recorded energy consumption data/records for years 2005-2008. In the same table are also shown and the results produced using two other known methods obtained from technical literature in order to compare the accuracy of the developed method.

The first method uses the linear regression model of equation (2), which is presented in detail in both [4] and [11].

$$y = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_3 + a_4 x_4 + e \tag{2}$$

where y is the final energy consumption, α_i the regression coefficients (i=0,1,2,3,4) estimated using a least square method, x_1 is the yearly ambient temperature, x_2 is the installed power capacity, x_3 is the yearly per resident electricity consumption, x_4 is the the gross domestic product and e is the random error term.

The second method is based on the support vector machine model introduced by Vapnik [27]. Based on this model, data is mapped into a higher dimensional feature space via nonlinear mapping and then regression in this

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space is performed. The function of (3) is estimated based on the given data set $G = \left\{(x_i, d_i)\right\}_i^N$ where x_i is the inputs, d_i is the desired values and N is total number of data sets.

$$y = \sum_{i=1}^{4} w_i \Phi_i(x) + b \qquad (3)$$

where $\Phi_i(x)$ is the set of mapping of inputs and w_i and b are coefficients. They are estimated by minimizing the regularized risk function (4) as presented in detail in [12, 13, 28, 29]:

$$R(C) = \frac{C}{N} \sum_{i=1}^{N} L_\varepsilon(d_i, y_i) + \frac{\|w\|^2}{2} \qquad (4)$$

where:

$$L_\varepsilon(d, y) = \begin{cases} |d - y| - \varepsilon & for \ |d - y| \geq \varepsilon \\ 0 & otherwise \end{cases} \qquad (5)$$

and ε is a prescribed parameter.

It must be mentioned that for the support vector machine model the C++ library libsvm (version 2.86) produced by Chang and Lin [30] has been used. C-classi1cation and ε-support vector regression has been applied for the estimation of the hyper-parameters based on the work presented in [30].

It is obvious that the results obtained according to the proposed ANN method for the four known years (2005-2008) are close to the actual ones and comparable to these produced by the regression and support vector machine models. Fig. 4 presents the comparison of the obtained results with the actual recorded energy consumption data. The percentage error between recorded final energy consumption and ANN computed final energy consumption given by (6) is approximately 2 % something which also clearly implies that the proposed ANN model is well working and has an acceptable accuracy.

$$PE\,(\%) = \frac{FEC_{rec} - FEC_{comp}}{FEC_{rec}} \cdot 100 \ \% \qquad (6)$$

where: PE is the percentage error, $FEC_{,rec}$ is the recorded final energy consumption and $FEC_{,comp}$ is the computed

final energy consumption.

6. Conclusions

The paper describes an artificial neural network method for the long-term prediction of Greek energy consumption. Actual recorded input and output data which undoubtedly affect significantly the energy consumption were used in the training, validation and testing process. Predictions have been performed for years 2005-2008, 2010, 2012 and 2015 with the produced results to be close to the real ones, much more accurate than these obtained by a linear regression model and similar to these obtained by a support vector machine model. The proposed approach can be useful in the effective implementation of energy policies since accurate predictions of energy consumption affect the capital investment, the environmental quality, the revenue analysis, the market research management, while conserve at the same time the supply security. The evolvement of the produced ANN model in a user friendly software tool with the addition of a graphical user interface could constitute it an important tool in the studies of electric utilities and regulation authorities in Greece offering an accurate prediction for the Greek long-term energy consumption.

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Vitae:

Lambros Ekonomou was born on January 9, 1976 in Athens, Greece. He received a Bachelor of Engineering (Hons) in Electrical Engineering and Electronics in 1997 and a Master of Science in Advanced Control in 1998 from University of Manchester Institute of Science and Technology (U.M.I.S.T.) in United Kingdom. In 2006 he graduated with a Ph.D. in High Voltage Engineering from the National Technical University of Athens (N.T.U.A.) in Greece. He has worked with various companies including Hellenic Public Power Corporation S.A. and Hellenic Aerospace Industry S.A., while in 2008 he was appointed Assistant Professor in ASPETE-School of Pedagogical and Technological Education. His research interests concern high voltage engineering, transmission and distribution lines, lightning performance and protection, stability analysis, control design, reliability, electrical drives, forecasting and artificial neural networks.

Fig.1 MLP feed forward artificial neural network.

Fig. 2 The Greek final energy consumption and gross domestic product from 1992 to 2008.

Fig. 3 The Greek installed power capacity and yearly per resident electricity consumption from 1992 to 2008.

Fig. 4 Comparison of the predicted with the use of the ANN and regression model Greek energy consumption with the actual one.

Table 1

MLP ANN input and output variables

Input Variables	Output Variables
- yearly ambient temperature T	- final energy consumption F
- installed power capacity C	
- yearly per resident electricity consumption R	
- gross domestic product G	

Table 2

Designed MLP ANN model architectures

Structure	Backpropagation learning rule	Transfer function
- 1 to 5 hidden layers	- Gradient Descent	- Hyperbolic Tangent Sigmoid
- 2 to 100 neurons in each hidden layer	- Conjugate Gradient	- Logarithmic Sigmoid
	- Quasi-Newton	- Hard-Limit
	- Levenberg-Marquardt	- Competitive
	- Random Order Incremental	- Linear

Table 3

Training data of designed ANN models

No.	Structure	Backpropagation learning algorithm	Transfer Function	Epochs	Train Error	Validation Error
1	4/20/17/1	Leven.-Marq.	Log. sigm.	13,318	0.010	3.52 %
2	4/21/15/1	Grad. descent	Log. sigm.	14,683	0.010	4.70 %
3	4/15/15/1	Grad. descent	Log. sigm.	15,000	0.024	4.89 %
4	4/19/22/1	Leven.-Marq.	Hyp. tang. sigm.	13,164	0.010	5.16 %
5	4/14/13/1	Grad. descent	Log. sigm.	14,281	0.010	5.08 %
6	4/13/17/1	Conj. Grad.	Hyp. tang. sigm.	15,000	0.036	6.99 %
7	4/23/1	Leven.-Marq.	Hard limit	13,803	0.010	8.32 %
8	4/12/14/1	Leven.-Marq.	Hyp. tang. sigm.	15,000	0.026	9.79 %
9	4/16/17/1	Leven.-Marq.	Log. sigm.	15,000	0.033	11.24 %
10	4/23/25/1	Grad. descent	Hyp. tang. sigm.	14,362	0.010	12.62 %

Table 4

Results of the proposed MLP ANN model

Year	Final Energy Consumption (1000 TOE)			
	ANN results	Regression model results	Support vector model results	Real records
2005	21,032	21,589	20,514	20,800
2006	21,964	23,116	21,748	21,454
2007	22,755	23,294	22,804	22,552
2008	23,239	23,341	23,107	22,986
2010	26,043	26,223	25,939	-
2012	28,410	28,713	28,372	-
2015	31,963	32,468	32,894	-
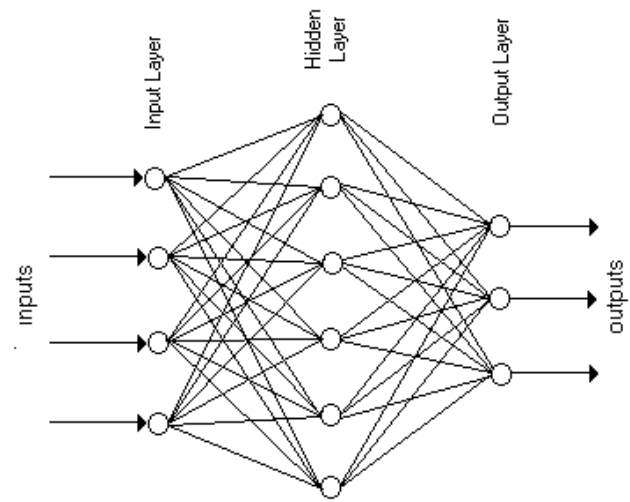
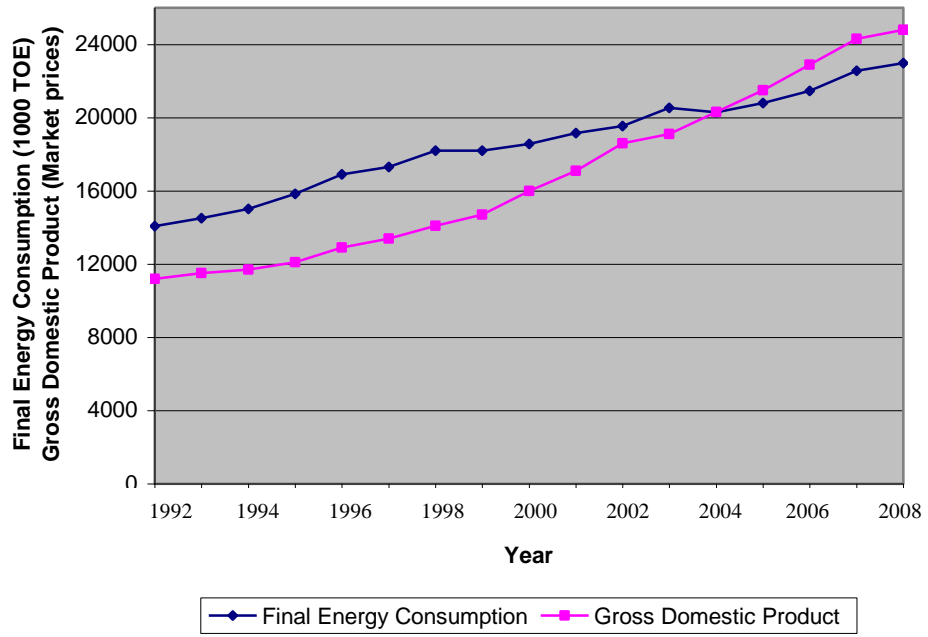Fig.1 MLP feed forward artificial neural network.

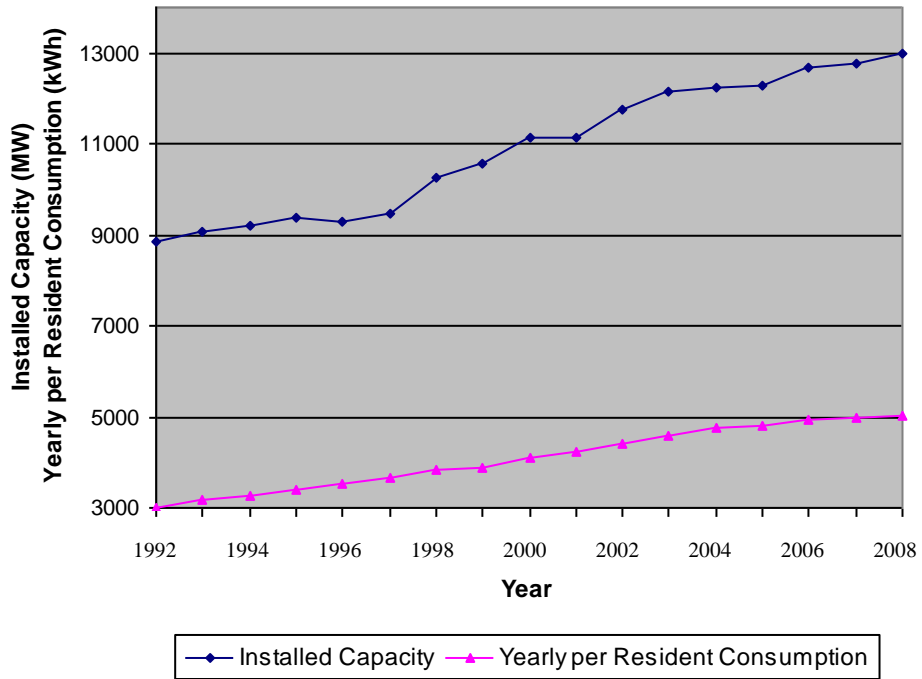Fig. 2 The Greek final energy consumption and gross domestic product from 1992 to 2008.

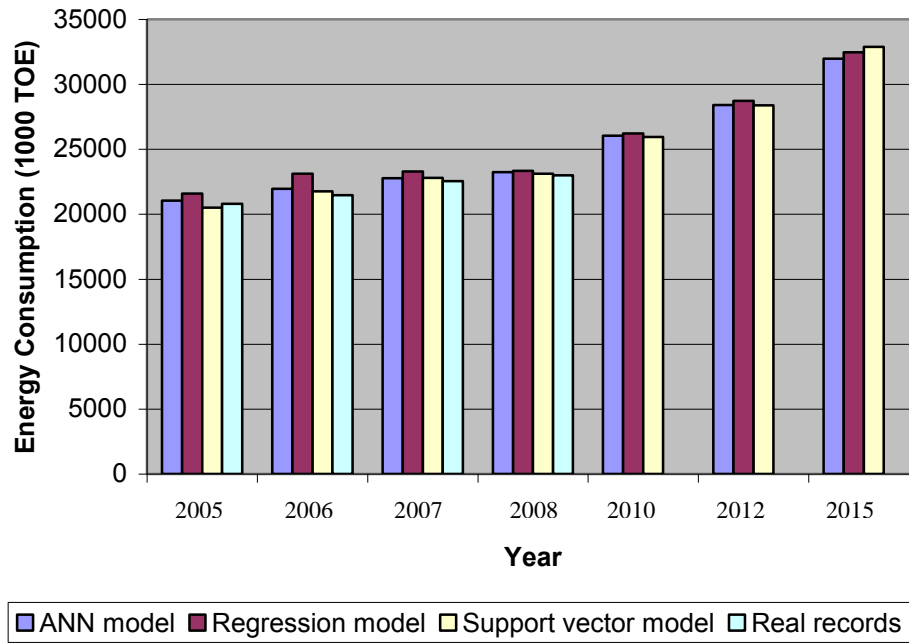Fig. 3 The Greek installed power capacity and yearly per resident electricity consumption from 1992 to 2008.

Fig. 4 Comparison of the predicted with the use of the ANN model, the ~~and~~ regression model and the support

vector machine model Greek energy consumption with the actual one.