

# WEB-BASED ENERGY INFORMATION SYSTEM FOR OPTIMAL BI-DIRECTIONAL BEHAVIOURAL CONTROL OF VARIOUS ENERGY CUSTOMERS USING ADSL HYPERCUBIC CLUSTERING AND INTERNET SERVICES (EMIR System)

Vassilis Nikolopoulos , PhD Candidate NTUA

Vassili Loumos, Professor NTUA

Multimedia Technology Laboratory

School of Electrical and Computer Engineering

National Technical University of Athens

Athens, GREECE

[vnikolop@medialab.ntua.gr](mailto:vnikolop@medialab.ntua.gr) , [loumos@cs.ntua.gr](mailto:loumos@cs.ntua.gr)

## ABSTRACT

Internet use, domestic energy consumption for electricity, renewable energy production, consumers' education and their interaction are focused in this paper. The increasing number and speeds of internet connections can be seen as the tool for measuring electricity and consumers' behaviour on energy consumption, giving an added value to consumer access and interactive approach to energy and energy related solutions. An increasing number of consumers from all levels of the society, cultures, lifestyles and social status have continuous internet access through ADSL connections. Those consumers will be targeted in order to collect and analyse their acceptability in new energy technologies.

The aim of this paper is to develop an internet-based methodology that brings together energy consultants, domestic consumers and renewable technologies. Consumers' interaction with energy consultants will be a valuable step into implementing efficiently EU policies, focusing on the introduction of informative billing through end-use energy efficiency directive and the use of renewable energy sources. Furthermore, the involvement of utility companies [6] will be valuable in order to manage efficiently electricity production and to plan demand side management and energy efficiency programs. Energy-related market will be enforced and benefited through targeted information, behavioral changes and innovative accessibility internet tools.

## KEY WORDS

Energy Information Systems, Hypercubic clustering, energy location-based services, energy decision support systems, ADSL Energy management

## 1. Introduction

A modern Decision Support System (DSS) can be defined as computer-based tool, or a more complex Information System structure, used to support and generate decision-making and problem solving. Although this definition

applies very well to decision-making [8] in many purely technical areas, it falls short of reflecting one extremely important aspect of the decision-making process in water resource systems: the role of human factor. Energy Information Systems (EIS [3]), which monitor and organize customer energy consumption and related trend data over the Internet, have been evolving over the past decade and can be considered as a part of a specialized DSS. The above concept performs key energy management functions [3] such as organizing energy use data, identifying energy consumption anomalies, managing energy costs, and automating demand response strategies and focused customer profiling. In this paper, a modern and innovative web-based intelligent Energy Information System [1], [7] is briefly described, for an optimal energy sources management and minimisation-control of home and factory-based energy consumption (**EMIR system - Energy Management & Intelligent Reporting**).

## 2. Energy Information Systems

The method is used for effective Energy Knowledge management in the newly opened Greek Energy Market. The system is designed and developed to analyze, optimize and manipulate energy data and energy practices, through a web portal. The energy data are accessed from ADSL-based databases and hypercubic grid structures or from internet-based heterogeneous sources, by using web Internet services. The system adopts a powerful combination of current software frameworks based on the J2EE specification.

Dynamic Java Server Pages and XML-XSL technologies provide effective energy data interoperability. The core intelligence of the on-line web system was developed using Matlab programming and the powerful MATLAB Web Server, connected in a clustered n-tier network. The system, which is currently on-line, was tested with real energy data and statistical graphical outputs were

produced for result analysis and web-based reasoning demonstration.

As back-end knowledge management procedure, a powerful clustered hypercubic isomorphic topology is used for the first time, with the additional use of traditional database technology.

This web-based functionality can be enriched with many add-on services in order to create a complete Information System that will act as the basic “ad-hoc broker” between free customers and energy providers, in the future opened Energy market

### 3. Brief Mathematical Modeling

A typical electricity demand model [10], [11] that we wanted to capture in our model includes four very important EPIs (Energy Performance Indicators) metrics: *elasticity*, *seasonality*, *mean reversion*, and *stochastic growth*.

- **Load Elasticity:** We assume electricity demand to be completely inelastic (i.e. independent of market clearing price). This may appear to be a strong assumption, but in the current state of deregulation, few end users actually observe real time price movements.
- **Load Seasonality:** Seasonality is a major driver for electricity demand. We observe seasonality over the daily, weekly, and yearly cycles.
- **Load Mean reversion:** One can observe temporary spikes in electricity demand, often induced by extreme weather conditions. However, these spikes are not sustainable and demand reverts back to normal levels within a few days.
- **Stochastic growth:** Growth in electricity demand is driven in part by trends in the overall economy. The growth is therefore hard to predict over longer time horizons, and must be considered stochastic.

The typical load vector  $\mathbf{L}_D$ , comprised of various daily load vectors  $\mu_m$  can be described by using the following

$$\text{formula: } L_D = \mu_m^L + \sum_{i=1}^j w_d^{Li} v_m^{Li} \quad (1)$$

where the set of principal components [10]  $v_{Li}$  and associated weights  $w_i$  is included so that the best approximation of the load vector  $\mathbf{L}_D$  is effectuated.

A monthly [24x1] vector  $v_{Lm}$  is used to describe load behaviour, reducing the load equation to:

$$L_D = \mu_m^L + w_d^L v_m^L \quad (2), \text{ where } \mu_m \text{ and } v_m \text{ are deterministic parameters and } w_d \text{ is a daily stochastic process. The choice of the number of principal components used is a trade-off between accuracy and}$$

complexity. For short-term decision, making such as day-ahead bidding, a single PC may not provide a rich enough sample space. However, when applying the price process to hedging and valuation decisions over months or years, a small basis prevents the problem from blowing up in computational complexity. Next, we must include and take into consideration the mathematical model that describes the new energy open-market. Load prediction and the above load formulas will be incorporated into the general overall function and this term will play an essential stochastic role to the overall estimation and decision process. According to *Lekatsa's model* [4], the main Energy Equilibrium Function (EEF) is described by:

$$\sum_{j=1}^n (Q_j - L_\Delta - L_E) * SMP + \sum_{i=1}^m (Q_i^a - L_i^a) * SMP = 0 \quad (3)$$

where Load  $L_\Delta$  and  $L_E$  can be modeled and estimated by equations (1) and (2) and represent the load consumption and  $Q_i$  represent the generated or imported load from the potential Energy producers or Energy Sellers and SMP is the System's Marginal Price. The difference  $Q_i - L_i$  is a very important metric that can represent and describe the gain margin of any potential Energy provider. Thus, energy estimation and prediction is very crucial and it is one of the main functions that this web-based Energy Information System can perform, by grouping and clustering various energy customers and consumers in order to form dynamic customer-based energy profiles and clusters. Those energy clusters are combined with a semantic network to produce realistic statistical predictions, based on equations (1), (2) and (3). As the main objective function [4] for the on-line optimisation procedure taking place inside the EIS, equation (3) was used.

### 4. Matlab Server & Energy Programming

Matlab has documentation based on external interfaces describing how to call m-files from C/C++ /Fortran/Java & C#. Developer can easily access matlab through Component Object Model (COM) and Dynamic Data Exchange (DDE) support at Microsoft Windows based platforms. Also, there are built-in C Routines to call matlab from other languages. These routines are accessible for both Microsoft Windows and all POSIX based (Linux, UNIX like) operating systems. C and C++ languages are not well formed and not a rapid choice for developing N-Tier applications (for example, Remote Method Invocations and Web Services) like C#. As long as it seems C# on .NET Framework is a suitable solution, C# can only implement C or C++ routines in unsafe blocks, which cause stack overflow. It can be accepted as a satisfactory solution, Java Native Interface (JNI) technology can wrap C routines in Java. On the other hand, Matlab has a product called “MATLAB Compiler” to generate runtime [5] based DLLs, C# Assemblies or Java classes to use m-code in C, C++, C# or Java. Main

purpose is to reduce time in development and easy code management. Besides, m-Compiler has limitations and restrictions. The developer may face with challenges in this solution. There are some approaches that use C Routines of Matlab to overcome this issue. One of them is a toolbox called MATLAB Web Server [5]. MATLAB Web Server use Common Gateway Interface (CGI) to transfer data from web to MATLAB. Matlab Server Pages [13] (MSP) is an open source technical web programming language using matlab engine in background. MSP supports “3-Tier Architecture”; Web Tier, Business Tier and Database Tier. Also, MSP consists of “distributed computing” and “parallel processing” via remote procedure calls and web services. MSP uses JavaServer Pages technology to define Custom Tag Libraries, called Matlab Tag Library Definitions (TLDs) & MATLAB Remote Method Invocation (RMI). TLDs, to handle a rapid application development (RAD) environment for web developers. Underlying Java RMI support acts as a gateway for distributed computing and parallel processing. Thus, MSP can use a remote Matlab just like on local computer. MSP implements JavaServer Faces for defining business logics and business rules including advanced UI components. MSP includes Web Service Definition Language (WSDL) files provide an opportunity for using MATLAB as a Web Service. MSP is Business Process Execution Language (BPEL) and Web Services Interoperability (WS-I) standards compatible.

In general, MSP architecture can be summarized as follows:

- MATLAB Server Pages connects to matlab engine with Stefan Mueller’s Java Wrapper Class called JMatLink [13]. MSP Java classes drive JMatLink for JavaServer Pages by adding new methods for matlab features, JSP page output, imaging on browser, remoting and web services
- By default, MSP comes with MySQL JDBC driver. JSP Standard Tag Library has SQL tag library, which can run SQL expressions on database server. Expression Language Mechanism handles MSP Tag Library and SQL Library interactions. From MSP, developers can connect to a database server. They can retrieve data from MATLAB and store to database and vise versa. This is the Database Tier - EIS Tier.
- JavaServer Faces is a technology that has advanced user interface components for JSP and can define navigation rules for business processes by running beans in background. MSP uses Apache Software Foundation MyFaces implementation. The pages that use JSF have MLSPX extension in MSP.

Default extension is MLSP for MSP. MLSPXs can call beans and do operations defined in them. Developers can add their beans to MSP. Matlab Beans (m-beans) work like a Plug-in Logic. If developers use remote-methods in Matlab Beans, they can separate business logic and

business rules to another server. This puts “Business Tier” to forward. MSP has several demos and examples on how to use MSP Engine. Client systems can be dynamic web pages, a part of distributed computing and web service operations. These usage examples can be called as a “Client Tier”.

Main Classes have several methods to handle custom JSP Tags at Web Server. For example:

<Matlab:Engine> tag on Web Server runs:

```
public void engineOpen() {
    // Reads MSP settings from Bundle.
    ResourceBundle rb =
    ResourceBundle.getBundle("MSP");
    // Code Dir is the base for MATLAB
    M-Files, Simulink Models and
    // Matlab Server Files. All
    runnable codes and models must be
    // there.
    Code_Dir =
    rb.getString("Code_directory");
    // Image Dir is the base for
    MATLAB created images.
    Image_Dir =
    rb.getString("Image_directory");
    // System out out for Java debugger.
    System.out.println("MATLAB Server
    Pages Engine");
    javaLink = new JMatLink();
    javaLink.engOpenSingleUse();
    // Running MSP at Code Dir.
    javaLink.engEvalString("cd '" +
    Code_Dir + "'");
}
```

This class handles all RMI operations, database connectivity, distributed computing, and web services.

Web Server Layer acts as a RMI Client to connect to Application Server. This Web Server has a Remote Method Invocation Interface to MSP Main Classes located at Application Server. This interface includes all methods in these classes. So application in this server can use all functionality of MSP as running on local. Programmers can deploy applications on this server with an easy syntax:

```
test.mlsp
-----
<html>

<head>
<%@ include file="/Scripts/header.inc" %>
<title> Hello World! </title>
</head>
<body>
<Matlab:Engine>
    <Matlab:Command cmd="rand(1,10)"/>
    <Matlab:WriteData name="ans"/>
</Matlab:Engine>
</body>
</html>
```

The Web Server connects to Database Server Layer to exchange data using JSTL SQL Library and MSP Tag Libraries.

## 5. Technical Architecture of EMIR System

In order to show and describe the functionality of the Matlab Server Pages (MSP), a web-based Energy Decision Support System (MSP), a web-based Energy Decision Support System was used in order to integrate Matlab functions and tags to the energy analysis procedure. A modern Decision Support System (DSS) can be defined as computer-based tool, or a more complex Information System structure, used to support and generate decision-making and problem solving.

In a typical EIS architecture [3], [6], the EIS server hardware and software located at the EIS service provider's physical site record interval data via the Internet. The EIS receives these data from signals dispatched by meters installed in a customer's building, or directly communicates with meters. The EIS users can access the server with a password, and access the archived energy data either in real-time or in hourly, or daily updates from anywhere via a web browser.

This web-based functionality can be enriched with many add-on services in order to create a complete Information System that will act as the basic "ad-hoc broker" between free customers and energy providers, in the future opened Energy market. Two different environments were involved in the development of the web-based evaluation tool interface: hyper-text markup language (HTML) standards with the addition of some java server pages (JSP) under J2EE specifications, and advanced Matlab code [5], which permits the dynamic mathematical development of the evaluation model described above. The Matlab web server toolbox [5], [7] was effectively used by combining java language, to produce dynamic Matlab server pages [7]. The communication was preserved, through internal java objects, which are incorporated in the apache tomcat server. Remote Matlab method invocation was achieved by this way and by combining CGI-based POST methods to the Matlab web server; a very powerful Matlab application server was produced. The developed system allowed the creation of compact programs, called Matlab beans and the execution of those interconnected beans.

The application, using web GUI facilities sends data, through java calls and post methods to the Matlab beans and vice versa. The system support parallel processing algorithms and form the first simulations that took place in Medialab (NTUA), matlab parallel toolbox was used, in order to parallelize norm distance calculation. By using Valiant algorithm, internal package blocks where minimized statistically.

The overall performance output was more than positive, allowing the algorithm to be executed concurrently to any energy customer, using special screen-saver programs.

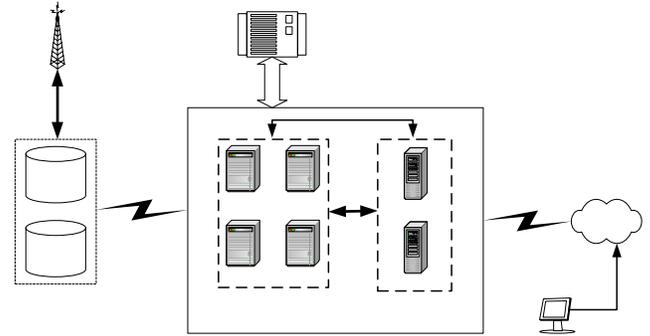


Fig. 1 EMIR System Technical Architecture

## 6. Algorithmic Background in Hypercubes

The method for analysing energy data and moving towards a decision (patented method and system by two patents so far) uses a different version of a clustering algorithm and a hypercubic grid [2] in order to cluster energy pages and energy measurements in a distributed way, not only by an energy count analysis but using a relevance distance calculation method from an optimal value, which is called hypercubic centroid. The probable energy pages or measurements that will be used to measure normed distances form a surrounding grid in a multidimensional binary space. For each possible energy measurement that is going to be assessed, we choose and construct an attribute vector describing some attributes that we have to take into account in order to decide if the page is relevant with a specific query. After the formation of the attribute vector, we assign weights ( $w_i$ ) to the

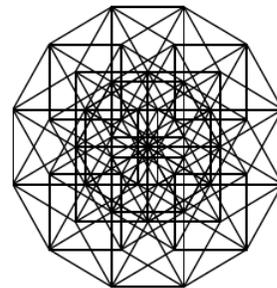


Fig. 2 A 64-dimensional hypercube grid

attributes to distinguish the most important and we choose possible optimal values (optimal energy pages) that are described by various optimal attribute vectors. These optimal values are the centroids. After the formation of the centroids, we start to measure metric distances (*calculation of p-norm*) from each centroid and all the possible pages that we have gathered (*energy crawlers*) through internet (*identical to indexer*). This can be achieved by a hypercubic parallel network with moving agents, where the centroids are the vertices of a multidimensional hypercube. With this method, we create relevance tables for each centroid and the total system is

called Hypercubic Knowledge Grid (HNG). The algorithm generates the knowledge grid and by using search algorithms we can access the relevance tables and rank output data according to a specific query. The above algorithm will be also used for Data bases analysis and SQL query optimization. The above mentioned method, helps us a lot in order to assign different optimal values to the various vertices of the hypercube and take these values as optimal centroid solutions for a multidimensional data mining application that has as a result, ranked sets of information retrieval queries. In order to perform a distributed data mining and clustering algorithm inside a hypercubic network, we need to ensure that parallel communications between vertices follow some structured rules and that ranked output data will be available.

A hypercube with dimension N, (GH (N)) is a network grid having  $2^N$  binary vertices which are mapped on a binary space. The distributed agent hypercubic scheme that will be used in order compute the normed energy distance between an optimal centroid solution and a multidimensional energy vertex that represents a possible query to the energy search engine, will follow the above structure and a method of the probabilistic routing algorithm of Les Valiant [2]. We will define a probabilistic random vertex permutation  $\Pi$ , using a uniform distribution. In each vertex there exists an agent that will measure the  $n$ -th dimensional topological norm between the vertex and the optimal centroid.

The above mathematical procedure is being used in order to calculate all the topological distances between centroids and relevant vertices, by using hypercubic routing and distributed agents. The results of the calculations form a uniform multidimensional table which is called Energy Relevance Table. This table represents the degree of relevance of each vertex from the surrounding grid comparing with a unique optimal centroid (hypercubic node), which can express an optimal solution, an optimal value or a suggested value to a problem or an Energy query [8].

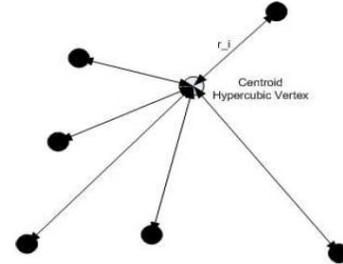
In each cycle the algorithm will compute the normed distance between each local vertex (optimal centroid) that the agent resides in each cycle and the surrounding grid of possible solutions from the query. A multidimensional relativity matrix will be created with all the normed distances between the centroid vertex and the surrounding grid. After the determination of the local matrix the agent moves to the next vertex, defined by the routing algorithm.

The computational complexity of the above hypercubic-based algorithm was computed by using the Chernov born. We will have to add the computational load for calculating the  $p$ -th dimensional norm for each vertex, which of course depends on the dimension of the surrounding grid (ie. Dimension N).

As it was mentioned above, relativity measurement between an optimal centroid and a probable value from the surrounding grid, can be achieved by measuring the metric distance between these two vertices. The distance

$r(\cdot)_p$  can be mathematically represented by the  $p$ -th topological norm  $\|\cdot\|_p$ , inside the hypercubic space.

Lets consider the graph below, showing a centroid  $c_i$  and 6 possible values  $x_1 \dots x_6$  of dimension 4 (4 attributes describing each vertex), from the surrounding grid. In order to calculate the distances  $r(c_i; x_1); r(c_i; x_2) \dots r(c_i; x_6)$  between the centroid and each value, we compute the mathematical expression shown below, in a recursive loop.



$$r_i(c_i, x_1) = \|c_i, x_1\|_p$$

$$r_i(c_i, x_2) = \|c_i, x_2\|_p$$

$$r_i(c_i, x_3) = \|c_i, x_3\|_p$$

$$r_i(c_i, x_4) = \|c_i, x_4\|_p$$

$$r_i(c_i, x_5) = \|c_i, x_5\|_p$$

$$r_i(c_i, x_6) = \|c_i, x_6\|_p$$

So in order to take the  $p$ -th dimensional norm of the local vertex, we have to sum the 4-th dimensional difference attribute vector of each vertex, comparing with the centroid, such as :

$$r_i(c_i, x_i) = \|c_i, x_i\|_p \Rightarrow \left[ \sum_{j=1}^{n=4} (c_i, (x_i)_j)^p \right]^{1/p} \quad (4)$$

Where  $p \rightarrow N$ , which is the hypercubic dimension.

As mentioned before, the results of the calculations form a uniform multidimensional table which is called **Energy Relevance Table**.

This table represents the degree of relevance of each vertex from the surrounding grid comparing with a unique optimal centroid (hypercubic node), **which can express an optimal solution, an optimal value or a suggested value to an energy problem or a query**.

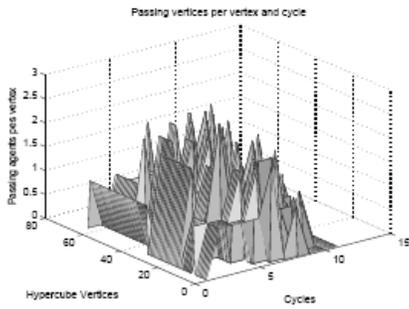


Fig. 3 A 64-dimensional hypercube Simulation in Medialab

## 7. Case Study and Graphical Examples

The system (<http://fermat.medialab.ntua.gr/emir>) was tested with real energy data, from DESMIE (<http://www.desmie.gr>) using the previous year's energy data repository for the National Energy Consumption database 2004-2005, using the National Load (MWh) and the extracted SMP (Euros/MWh). The system has a web-based Graphical User Interface, that lets the consumer or the producer to control the directed queries on the energy database. There is a functional menu with all available functionalities. The user simply selects the option and by pressing a key, the system generates useful graphs (Fig. 6) and various customised measurement tables with statistical data.

Also, special measurements from Greek Home consumers were used, in order to analyse and correlate energy behaviours along time. Energy data were measured successfully from various electrical devices inside the house, using PLC modems. This gives advantage to the system, since many statistical and stochastic correlations between home devices and load can be made, in order to extract correlated energy behaviours.

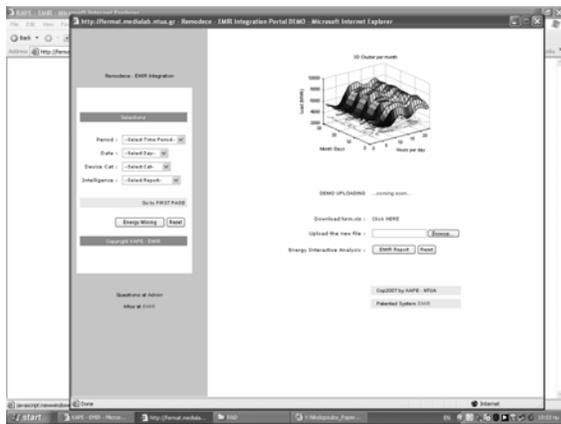


Fig. 4 The web interface of EMIR System for Energy management

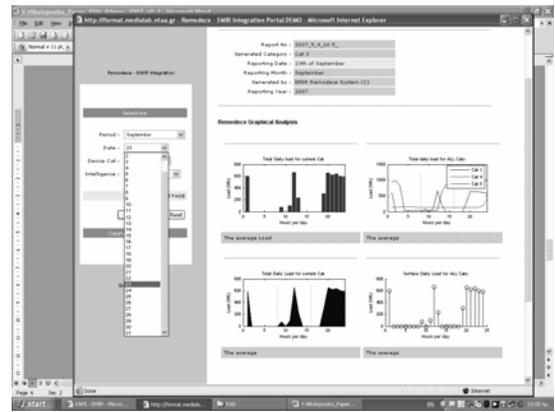


Fig. 5 Correlated energy behaviours of 3 devices during one day

The web-analysis showed an extreme efficiency in analysing and correlating home loads. As it can be seen from Fig.5, three electrical-home devices were stochastically correlated (AC function with co-variance matrix measured). The output of the hypercubic clustering, by setting as centroids optimal values for three devices (fridge, PC, TV) was taken and produces on screen by Internet MSP.

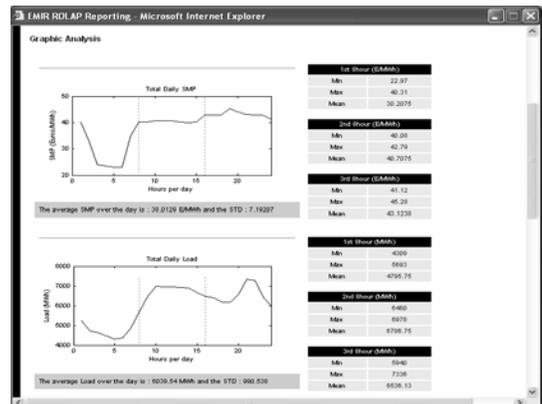


Fig. 6 National Energy consumption (Greece) in October 2006

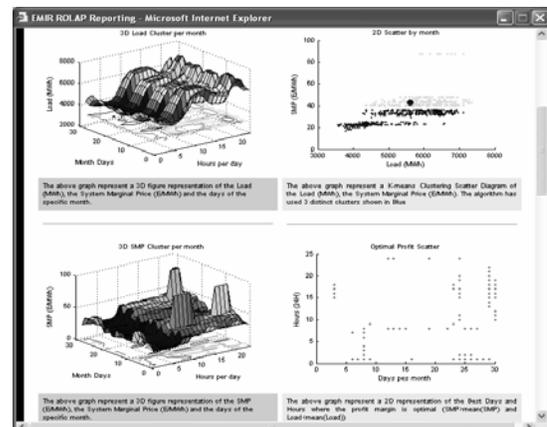


Fig. 7 Three dimensional Energy Graphs with k-means Clustering

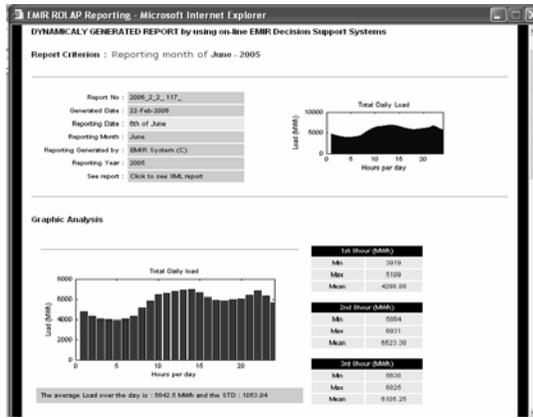


Fig. 8 Monthly Statistics for Greek Energy Consumption in 2006

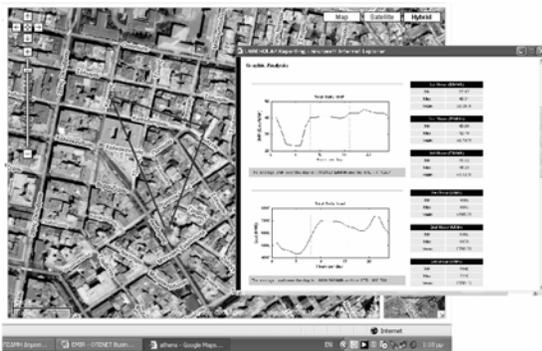


Fig. 9 Energy Location-based Services in Athens for energy geo-correlation of random Energy Customers

Finally, as it can be seen from Fig.9, we succeeded in embedding the above system an method into Google Maps API and producing geographical correlation of energy customers, according to their electrical profile. The output of the EMIR system (hypercube cluster) was mapped to a digital geo-database and a dynamic web-API was produced, mapping Google coordinates with energy consumptions. As a results, according to a home user consumption, his geo-map coordinate can be easily found and can be correlated with local geographical parameters (climate, location, GIS, etc). This will give new functionalities to the system, such as dynamic geo-correlation of home users, according to their correlated stochastic load.

## 8. Conclusions

So it can be said that traditionally most utility companies classified their customers according to a few electrical parameters and some commercial codes. In the liberalised electricity market, there is a strong need for classifying the electricity customers on the basis of indicators able to characterise their true electrical behaviour. A possible scenario of the interactions among customer and supplier could be the following:

- the customer comes to the supplier, states its type of activity and is assigned/free to choose a starting tariff; the supplier monitors the customer for a specified period (e.g., 3-6 months) and establishes a reference pattern for its load diagram;
- the supplier fits the reference pattern to one of the customer classes already defined and identifies the appropriate tariff;

Hence, the supplier performs a continuous monitoring of the daily load curves of all customers, periodically updates the reference patterns and the composition of the customer classes by automatic clustering and adjusts the tariffs applied to each customer class such as to maximise its foreseeable profits in the respect of possible price caps. Efforts to put some order in the tools to analyse the load diagrams have been produced for quite some years. We can mention the systematic approach used in UK [12], according to which several subclasses are defined within each major class of customers, for each of them a different tariff being assigned. This approach is backed by some extensive field measurement campaigns that span over two decades. A rather similar approach has been implemented in Taipei, together with a comprehensive survey system.

The load diagram associated to each average customer is the **load profile** of the corresponding customer class. The economical aspects related to the possible tariff diversification for the various customer classes are investigated by using the load profiles for providing suggestions on possible market strategies seen from the point of view of the electricity utility. Traditionally, most utility companies classified their customers according to a few electrical parameters and some commercial codes. In the liberalised electricity market, there is a strong need for classifying the electricity customers on the basis of indicators able to characterise their true electrical behaviour.

So it can be said that traditionally most utility companies classified their customers according to a few electrical parameters and some commercial codes. In the liberalised electricity market, there is a strong need for classifying the electricity customers on the basis of indicators able to characterise their true electrical behaviour.

## References

- [1] *E.M.I.R. Project (Energy Management & Intelligent Reporting)* : <http://fermat.medialab.ntua.gr/emir>
- [2] V. Nikolopoulos “Analyse et Simulation des méthodes de routage dans la topologie d’hypercube” mémoire, Ecole Polytechnique, promotion X99, 2002
- [3] RTE, France, “Responsable d’équilibre - Règles et contractualisation”

- [4] E.Lekatsas, "Financial Analysis of Energy Systems", Chap.4 Pupl. TEE 2000
- [5] The Mathworks Inc., 1999.  
*MATLAB Web Server. Natick, MA*
- [6] MAVIR website <http://www.mavir.hu>  
"Code of Commerce"
- [7] V.Nikolopoulos, V.Loumos, "A web-based Energy Decision Support System for dynamic knowledge energy management and automatic intelligent reporting (EMIR)" Paper under preparation, 2007
- [8] Newman MEJ. "The structure and function of complex networks", *Siam Rev* 2003;45(2):167-256.
- [9] Steyvers M, Tenenbaum JB, "The large-scale structure of semantic networks: Statistical analyses and a model of semantic growth" *Cog. Sci* 2005;29(1):41 78.
- [10] M.Emoult and F.Meslier, "Analysis and forecast of electrical energy demand". *RCE*, No.4, 1982.
- [11] Skantze, P., Chapman, J., Ilic, M.D., "Stochastic Modelling of Electric Power Prices in a Multi-Market Environment", *Transactions of IEEE PES Winter Meeting*, Singapore, January 2000.
- [12] S.V.Allera and A.G.Horsburgh, "Load profiling for the energy trading and settlements in the UK electricity markets", *Proc. DistribuTECH Europe DA/DSM Conference*, London, 27-29 October 1998
- [13] Ali Kizil, "MSP matlab server pages", <http://msp.sourceforge.net/>
- [14] V.Nikolopoulos, "EMIR - Energy Management and Intelligent Reporting" Bulletin of Electrical and Mechanical Engineers Bulletin, No 382, 1 December 2005 "
- [15] V.Nikolopoulos, V.Loumos, "A Web-based system for optimal Energy Sources Management, through Ontologies and Semantic Clustering" Technical Chamber of Greece (TEE) Research Conference 2006, Athens, Greece
- [16] Vassilis Nikolopoulos, Vassili Loumos, "A Web-based Information System for Optimal Energy Sources Management through Ontologies and Hypercubic Clustering ", Energy 2006 International Conference, Athens Greece
- [17] Vassilis Nikolopoulos, Vassili Loumos, "A Web-based Information System for Optimal Energy Management", T.E.E. Energy Minimization Research Day 2006, Academy of Sciences & NTUA
- [18] V. Nikolopoulos, Vassili Loumos "Integrated Ontological Model of web-based Energy Management through Semantic Hypercubic Grid", V, 2<sup>nd</sup> Panhellenic Conference of PSDMH in Athens, May 2007