# SCENARIO BASED ELECTRICITY LOAD PREDICTION TOOL FOR DISTRIBUTION PLANNING AND MANAGEMENT

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## *ABSTRACT*

*Methods for regional load prediction, capable of dealing with user-defined scenarios, are required in planning and managing electricity distribution networks. In this paper, the concept of scenario based tool is presented for the prediction of regional electricity loads in heating system scenarios. An innovation of the tool is that of self-organizing map (SOM), which is used to allocate AMR originated load curves between customer groups based on building information. Furthermore, rich internet application (RIA) based on ArcGIS Server, Matlab and Silverlight web application framework is presented.*

## INTRODUCTION

The increasing adoption of renewable energy sources, such as ground and air heat, solar energy, wind power and bioenergy, in distributed energy production (DER) has an influence on regional electricity demand which should be carefully considered in the planning and management of future electric power distribution networks. Methods for forecasting of regional loads have been developed, covering various temporal and spatial scale i.e. short, medium or long term forecasts on neighborhood, municipal or national scale. In strategic planning of the networks, the estimation of the future needs must be made on long term. This can mean predictions spanning from 1 to even 30 years ahead. Most of the models however, are developed for short or medium term forecasts which serve better daily or weekly management decisions [1]. Intuitively a conclusion can be drawn that, the longer time span a prediction covers, the more uncertainty it involves.

Usually models based on quantitative methods, which try to forecast the future accurately, have been the most common ones. However they are criticized for their poor performance on long term forecasting. The results of pure quantitative methods have been particularly unsatisfactory in cases where there are complicated and surprising phenomena of the society involved [2]. One way of controlling the inherent uncertainty, that is always present when making predictions or forecasts, is to analyze various possible decisions, events and their consequences more closely. Scenario analysis is a technique that fills this requirement. Scenarios are alternative views of possible future events and their outcomes. It is different from predicting and forecasting in that the aim is not to produce only one correct outcome but to present many different alternatives by analyzing possible future prospects. Scenarios stress especially uncertainties which are not controllable. Thereby it is possible to better take into consideration the new unknown factors that a pure statistics-based model could never anticipate. Many long term forecasts are done by taking into account different scenarios, but to really harness the full potential of the approach, it should be possible to quickly and conveniently produce a series of “what if?” –type experiments.

Often the modeling of load growth as a whole is not based on realistic regional estimations. For example, so far two commonly used network information systems in Finnish electricity companies have considered the load growth via global growth percentage which affects all the use sites and regions equally. In reality the load growth can have high geographical variation and without considering the changes on more specific regional level the modeling error can be significant.

When it comes to modeling the electric customer behavior, the prediction of hourly consumption habits of the customers is covered fairly well. Currently, approximated mean load curves are used for each customer group. In the existing situation the method is sufficiently good, especially when bigger group of customers are examined and the individual random behavior becomes evened out. Beside of this, there are customer groups having more random use of electricity causing difficulties to create proper common load curves. For these customers, individual load curves works better. Summer cottages and industrial customers are good examples of this kind of customers.

The current nearly static electricity pricing does not offer many incentives for the customers to change their behavior in a frequent manner. More dynamic pricing of the smart grid vision is bound to make the task of predicting hourly behavior more challenging. Load curves that are more dynamic will be needed respectively.

All in all, long-term prediction of regional load seems to be a challenging task, which requires the analysis of potential future scenarios and deep understanding of complicated behavior of customers and regions, and a combination of these issues in a sophisticated manner. Recent technological progress in small customer electricity metering, and resulting extensive AMR data sets combined with available external data sets, provide possibilities for the development of new advanced and reliable data-driven modeling approaches [3, 4].

In this study, the concept of scenario tool for the prediction of regional loads in different heating system scenarios is presented. Neurocomputing is applied as the part of the tool in order to identify complex interactions within the data. To demonstrate the scenario approach in practice, the RIA application was implemented using ArcGIS Server, Matlab and Silverlight web application framework.

## SCENARIO TOOL

The scenario tool developed contains the following major stages depicted in Figure 1:

(1) the selection of a target region and the definition of a scenario
(2) the allocation of new load curves
(3) the simulation of regional load
(4) the result interpretation using the web based interface

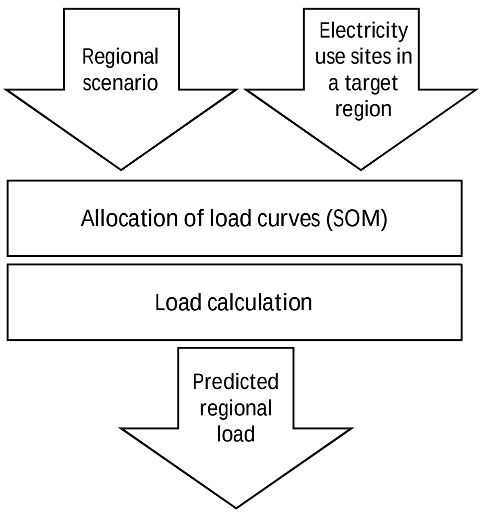


**Figure 1: Main stages of the scenario based modelling tool.**

In the first stage, a target region, for example, an urban/city or a rural area, is selected and user-sites located on this region are searched. This is followed by definition of a scenario concerning that region, i.e. definition of relative proportions of primary heating systems (district heating, oil, electricity, wood and heat pump) in a region. In the next stage, new load curves for user sites changing their heating system are allocated. After the allocation step, hourly loads are simulated over the year using user-defined annual temperature profile. The final stage consists of the examination of the loads using web based interface.

### Allocation of load curves

Allocation of load curves is performed based on the grouping of reference customers into similar groups expected to have similar load behaviour. Here the information derived from Finnish Population Information System (VTJ), maintained by Population Register Center, Finland, was used as the base data of the grouping. Variables included were: {total floor area and volume of building, age of building, structural material, façade material, primary fuel and heating system, number of inhabitants and age of inhabitants}.

Customers changing their heating systems are determined here straightforwardly using the random selection. However, this approach does not consider a probability of a customer to make changes in behaviour and hence leads into misleading equalization of customers. Therefore, further research is required for predicting which customers/regions are most probable to make changes in their behaviour. Many potential methods concerning this issue can be found in the literature [5, 6].

### Self-organizing map

Self-Organizing Map (SOM) is well-known unsupervised neural learning method, which is suitable for different complex data exploration tasks [7]. The aim of SOM is to find prototype vectors that represent the input data maintaining a continuous mapping from the input space to a lattice at the same time. The SOM learning is initiated by assigning random values to the weight vectors of the network. The training patterns are fed to the network one-by-one, and this procedure is repeated a pre-determined number of times (epochs) for each of them. At each training step, the best matching unit (BMU) is found by comparing the input and weight vectors of the neurons using Euclidean distance metrics. The weights of the BMU and its neighbours (according to the neighbourhood function) are then adjusted towards the input vector according to an update rule in which the learning rate factor decreases monotonically towards the end of learning:

$$w_m(t+1)=w_m(t)+h_{cm}(t)[x_i-w_m(t)] \quad (1)$$

where w is the weight vector, t is a counter for iterations, c is the index of BMU, m is the index for the neuron to be updated and h is the neighbourhood function which usually based on a Gaussian neighbourhood function:

$$h(t)=\alpha(t)\exp(-\|r_c-r_m\|^2/(2\sigma^2(t))) \quad (2)$$

where α(t) is a learning rate factor, rc and rm are location

vectors for the corresponding nodes and, σ(t) defines the width of the kernel, and α(t) is a learning rate factor.
In the approach presented, SOM trained on building information is used to allocate new load curves. Basic idea of the load curve allocation follows the principles of classification, i.e. the search of BMU and the determination of new load curve among a group of "reference" load curves belonging to BMU (Figure 2).

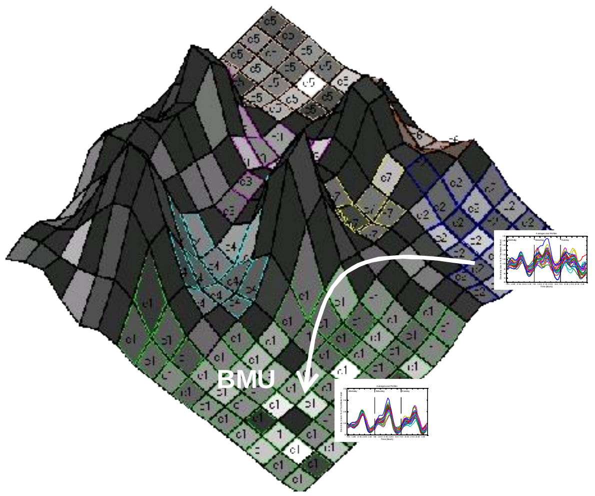


**Figure 2: Load curve allocation using SOM.**

## Load simulation

Customers' electricity needs varies from season to season, day to day, and even minute to minute. Therefore estimating the size and point in time of region-specific peak load is important. In this presented system annual peak load is one of the results and provided to decision makers and distribution management systems.
Simulation of hourly loads in a target region is performed using load curves reconstructed with aid of SOM+*k*-means and AMR data [8]. Load curves are based on 26 two-week profiles summarizing hourly electricity use separately for Weekdays, Saturdays and Sundays. Overall output of the simulation is annual hourly load calculated for each customer in target region and summed up into the spatial grids with 250 x 250 m dimension. Further analysis of the loads is then possible e.g. in respect to absolute hourly loads, proportional or absolute changes in loads or peak loads within defined time span.

## WEB APPLICATION

A web-based application was built using ArcGIS Server, Matlab and Silverlight web application framework (Figure 3). It enables the building up of regional heating system scenarios, the execution of scenario based calculations and finally the comparison of scenarios to each other using the web browser.
The web application was developed for IIS7.5 server as Silverlight application. Silverlight-framework enables to use rich internet application (RIA) functionalities, eg. layered map controls, rich graphic and different user dialogs.
Load simulation was implemented in server-side Matlab-session via special Web Services interface (WS). This interface allows user's scenario definition to pass on server side to be executed in Matlab.
Spatial functionalities of the application were implemented using ArcGIS Server and Silverlight API. ArcGIS Server was used to serve spatial data (use sites, electricity distribution network, background map) and to calculate sums of changed electricity use in selected target area.
Overall architecture of the web application is illustrated in Figure 4.

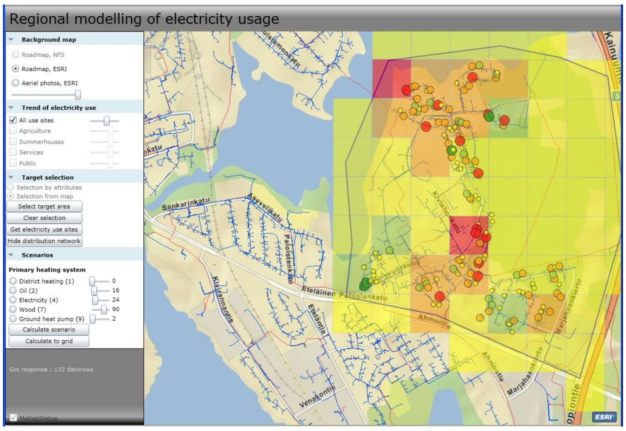


**Figure 3: Web interface implemented using Silverlight.**

## CONCLUSIONS

In this paper, the scenario based tool for the regional modelling of hourly electricity loads was presented. The tool is based on the allocation of AMR originated load curves between customer categories using site-specific building information. This technology and ideas would be part of strategic planning and managing systems of distribution networks. Further research is however required, especially in respect of:

(1) The investigation of methods for predicting which customers and regions are most probable to make changes in their behaviour
(2) Is there a real need for building characteristic information (increased costs) or is it possible to create feasible models based on other regional specific data
(3) How much of AMR data is needed from the target area and alternatively, is it possible to generalize the models from areas with more such data available
(4) Integration of the application with the existing network information systems, open interfaces and external databases

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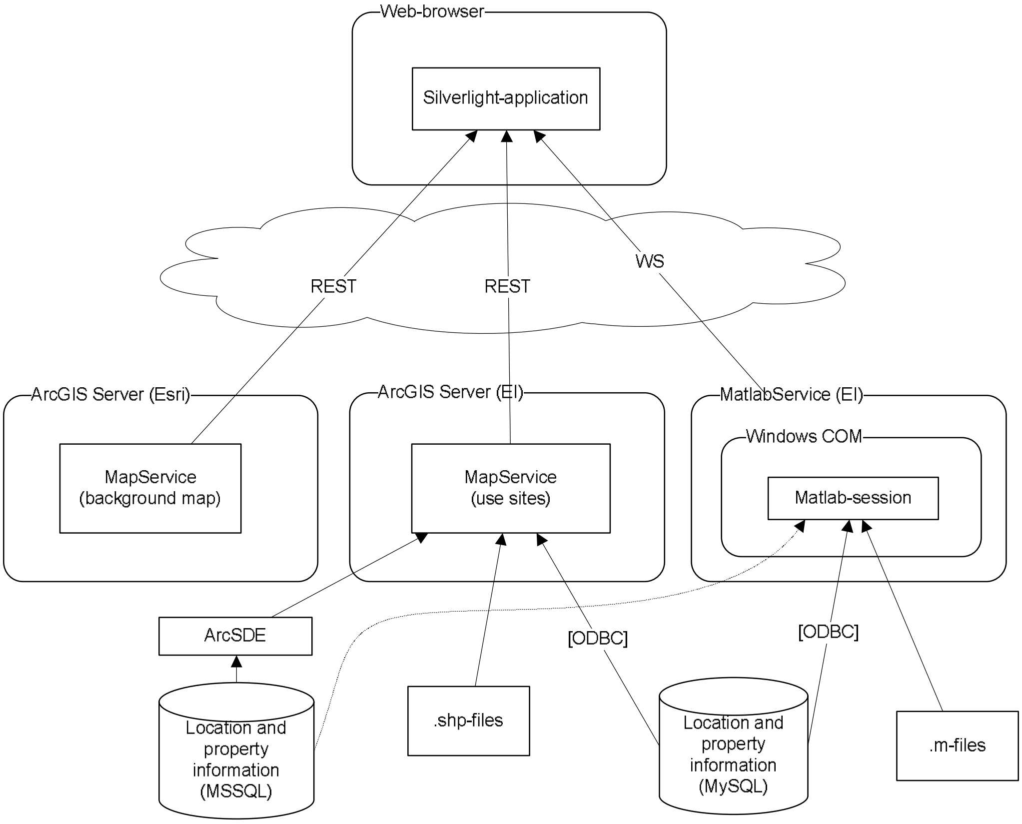


**Figure 4. Architecture of the web application.**