MODELING THE IMPACTS OF GOVERNANCE, SOCIAL AND URBAN FACTORS ON LONG TERM LOAD FORECASTING

Reza DASHTI
University of Tehran – Iran
rezadashti83@yahoo.com

Saeed AFSHARNIA
University of Tehran – Iran
safshar@ut.ac.ir

Shaghayegh YOUSEFI
University of Tarbiat Modares - Iran
yousefi_sh313@yahoo.com

ABSTRACT

In this paper, long term load forecasting is presented, focusing on external factors. Factors having impact on the load are categorized into three groups, namely: governance factors, social factors and urban planning factors. Subordinates of each factor are identified and quantified. Then, a data-driven model is constructed, having the external factors as inputs and peak loads and energy consumptions as outputs. Subsequently, the outputs of the model (i.e. peak loads and energy consumption) are utilized to calculate load factors. Using the developed model, sensitivity of the load factor is investigated versus the external factors. This can be used for self-governance of distribution company (DISCO).

INTRODUCTION

Distribution networks need to be expanded with load growth. Therefore, load forecasting is a crucial instrument for planning and forecasting future conditions of the network.

Load forecasting can be categorized as: short term, midterm, and long term[1]. However, by 'load forecasting', long term load forecasting is meant in this paper. Since long term network planning is considered here, so is the long term load forecasting.

Based on the foregoing, the bodies of research carried out can be categorized into two types:

Approach 1: Research and studies carried out, which are devoted to forecast load, by considering electrical loads of previous years. Consequently, it is necessary to apply an assortment of sophisticated algorithms to minimize errors. In this type, numerous studies and research have been conducted so far, and various methods have been innovated. [2, 3, 4, 5 and 6]

Approach 2: Research and studies have dealt with examination of factors influencing the load and study of those factors, as well as the extent to which they exert an influence. In this type, which comprises a limited portion of the conducted research, it has been tried to incorporate other factors as well in order to reduce forecast error.

In a majority of research, incorporation of such factors and establishment of load forecasting function accordingly has been carried out through application of ANN. [7, 8 and 9]. The more the selected load influencing factors are comprehensive; the fewer the errors in long term load forecasting will be.

A variety of load forecasting methods has been introduced with the aim of improving accuracy of load forecasting calculation. Regardless of the type and method applied for load forecasting purposes, the parameters incorporated in load forecasting are of very high importance. In fact, these parameter or the factors influencing load are sometimes more important than the load itself or the forecasted consumption. The reason is that the parameters which influence load forecasting can be used to gradually reduce marginal cost of future developments through managing and controlling them; moreover, such parameters are very useful for planning of urban distribution networks. However, in methods simply relying on historical load and consumption data, there is a high error probability, as well as the lack of control on peak load.

In this paper, taking all load influencing factors into account, it has been tried to forecast load with a lower margin of error compared with other methods. Besides, the trend of long term load fluctuations are monitored and evaluated in a much better way. The present paper is devoted to introduce a comprehensive method, which can incorporate all social and urban planning factors that exert an influence on load and consumption.

This paper is structured as follows:

Section 1 identifies and models all sorts of external factors that have an effect on long term load forecasting. Section 2 designs ANNs for peak load and energy consumption forecasting, versus the external factors. Section 3 presents numerical study by real data in Bushehr city and outputs are analyzed.

METHODOLOGY

Modelling factors influencing long term load forecasting

The two concepts of 'profile' and 'peak' generally attract consideration in load forecasting discussions. Thus, forecasting either of them has an enormous impact on the distribution companies' services and their managers' performance. Therefore, we have forecasted peak load and energy consumption to cover both of them.

The factors having impacts on load forecasting can be categorized into the following:

A) Governance factors

Subsidization is the only governance factor exerting an influence on electricity in urban areas. The degree of subsidization has a substantial impact on consumption behavior; consequently, investments on networks are also influenced considerably. The subsidization factor will be referred to by K1 hereinafter.

B) Social factors

This category encompasses factors which are highly influential on load forecasting; however, few comprehensive investigations have been made on them yet. This is important, because these factors influence on both load and its behavior. This category of factors itself can be subdivided into numerous branches such as marriage, reproduction, migration, housing value, age, education, occupation, etc; nevertheless, when dealing with a city from a holistic point of view, and considering homogeneity of social indices across a city, such factors can be categorized into four major topics requiring a social examination:

- Average family size (K2)
- Average income of each family (K3)
- Average value of residential units (K4)
- Awareness (K5). (This section includes general, legal, economic … awareness to electricity consumption.)

Any other social factor is either trivial from a holistic urban perspective or falls within one of the four above mentioned categories as a subset. To avoid repetition of the foregoing factors through the paper, the specified codes (K2, K3, K4 and K5) will be used for making references from now on.

C) Urban planning factors

Originating in urban governance and urban management system, these factors depend on numerous issues such as urban textures, urban structure, planning for housing, housing features, investment policies, construction density, citizens' participation, application alteration policies, etc. All these issues have been specified in urban master plans, and relevant policies have been defined for each of them in the prospect documents. Generally, the main indices from among such factors are as follows:

- Area (K6)
- Population (K7)
- Number of residential units (K8)

Any other urban planning factor is either too insignificant to deserve policy making or can be considered as a subset of one of the above mentioned factors. Surely, each of these three types of factors has distinct values, specified for different applications or zones across the city. However, we apply the values for the entire city as the load forecasting input. Besides, the above factors will be referred to, by the specified letters (K6, K7 and K8) in the rest of the paper.

Model architecture

The aim of analyzing the influencing factors in this paper is to calculate annual electrical peak load (K9) and annual energy consumption (K10). A generalized demonstration of these matters is depicted in Figure 1. Given the inputs and outputs of the "load forecasting model" box, its function is described in the following sub-section.

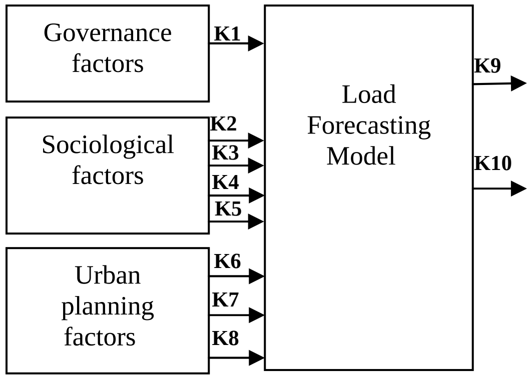

Figure 1. Inputs/Outputs of load forecasting model

The load forecasting model

Considering the models made in section (2-2) herein, inputs of the ANN system are K1 to K8. To obtain K9 and K10, two ANNs, separate but identical in terms of analysis functions and layers, are introduced. This ANNs are supposed to model eq.1 and eq.2.

k9=F1 (k1… k8) (1)

k10=F2 (k1… k8) (2)

In this paper, a multi layer perceptron (MLP) network is used for the purpose of load forecasting. The structure adopted here is a two-layered network, whose first layer's transmission function is linear, whereas that of its second layer is an arctangent. Besides, each layer contains five nodes and its output is adjusted to occur on a linear function. Of course, we should make sure that the data are normalized and then are trained to the network because normalization facilitates training process of ANNs.

In view of the foregoing, both neural networks can be demonstrated as in Figure 2.

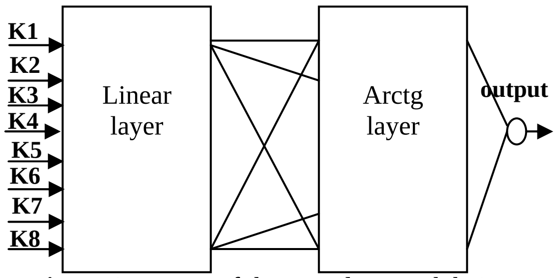

Figure 2. Layers of the neural network being used

NUMERICAL STUDIES

The distribution network of Bushehr city is chosen for implementation of the proposed model. Bushehr is the center of Bushehr province, located at the coast of Persian Gulf in Iran.

Implementation results

Once the training is completed, load and consumption data in 2017 will be as what appears in Table (1).

Table 1-The values of load and consumption in 2017 at presented model

year	k9	k10
2017	721.5653	307.1517

Evaluation and sensitivity analysis

In order to evaluate the accuracy of the proposed model, the peak of annual load in the year 2007 has been forecasted through two separate ANNs utilizing two training sets, load data of 10 years (1992-2002) and ones of 5 years (1992-1997). Dependability and efficiency of the applied model is demonstrated through the resulting error.

Sensitivity analysis evaluates the model and shows the effect of external factors on peak load and consumption, as well as the impact of ANN's training period on the gained results.

Impact of information period on load in 2017

To analyse such an impact, the initial data were considered to be in the three following states:

A. The data related to the indices of influencing variables during the years 1992-2002 are available.
B. The data related to the indices of influencing variables during the years 1997-2007 are available.
C. The data related to the indices of influencing variables during the years 2002-2007 are available.

With the following assumption, separate ANNs were trained and the results quoted in Figures (3),(4) were obtained.

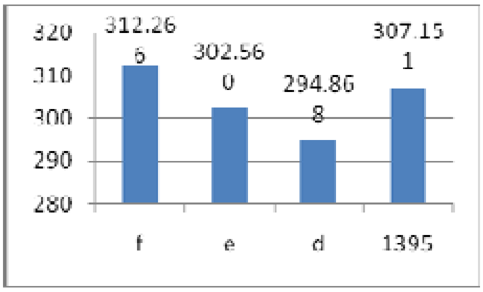

Figure 3. Load values with regards to analysis period

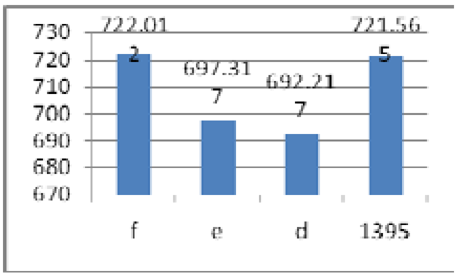

Figure 4. Consumption values with regards to analysis period

It is observed that the earlier the time period of index data are the lower load and consumption forecasted values will be; consequently, the results will be far from reality. Thus, planning will be carried out with some investment much lower than the required amount proving the plan inexpedient. As the time period of the data approaches the final year, the values approximate the values of the modelled mode with almost the same error. However, as the analysis time decreases, deviation in load and consumption values rises. As shown in Table (2), a shorter period of index data enhances the pace of analysis.

Table 2-Load and consumption deviation values in various periods

	D	E	F
K9	5.439348	6.863391	123.4467
K10	3.606245	17.46193	137.5697

Impact of various factors having an influence on long term load forecasting

Nevertheless, the following scenarios were taken into account in order to specify load and consumption forecast errors, regarding the following factors:

D. non-incorporation of subsidy (K1)
E. non-incorporation of subsidy and social factors (K1 to K5)
F. non-incorporation of the entire factors

In the mode E, the only factors were those of urban planning. Thus the method has much in common with 'land use' and 'end use' methods, yet it is more inclusive. In the mode F, none of the governance, social and urban planning factors were incorporated; rather, it was tried to carry out the calculations of the year 2017 solely based on the information contained in K9 and K10 (load and electrical consumption) during the years 1992 to 2007. This mode resembles regression method and other methods introduced in section 2, in which historical load and consumption data form the basis of future forecasts. Based on the foregoing, a separate ANN, yet of the same characteristic features stated in section 2, was trained and the results were obtained thereby. The results are delineated in Figures (5) and (6).

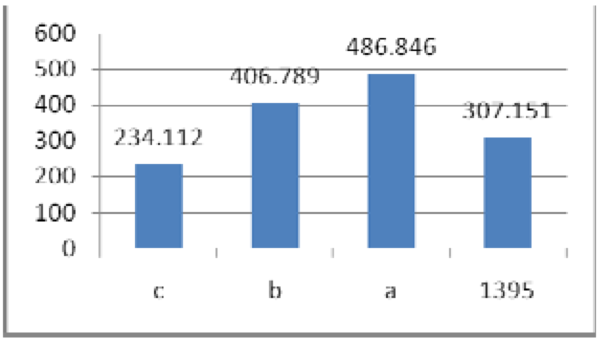

Figure 5. Load value calculated with some factors disregarded

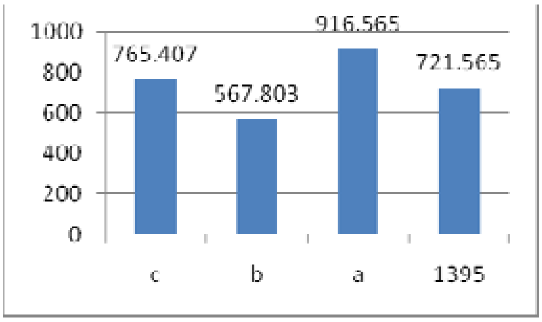

Figure 6. Consumption value calculated with some factors disregarded

As it is observed in Figures (6) and (7), mode (F) where forecast is carried out based on historical load and energy data, results in a planning with investment far less than what is required, hence proving the plan inexpedient. When comparing mode (D) and mode (E), it is understood that factors associated with urban planning have the most influence on load behaviour change, consumed energy and previous growth trend. Similarly, the mode D shows how situation can be improved by enhancing social indices. In fact, as social indices are improved, peak load decreases and the total energy consumption increases. Therefore, importance of social indices becomes more evident than ever by virtue of substantiality of such changes. Exclusion of none of the modes will not have a significant influence on the time of analysis, yet their deviations from the main mode are given in Table (3).

Table 3- Load and consumption error in 2017, completely modelled

	A	B	C
K9	56.60894	122.1009	51.64623
K10	246.6118	139.7271	31.00126

The load error index is calculated using eq.3.

$$\text{load error} = \sqrt{\frac{(L_i - L_T)^2}{2}} = \frac{L_i - L_T}{\sqrt{2}} \qquad (3)$$

Where:
Li is the load value in each of D, E and F modes (depending on the extent of error permissibility); and
LT: the load value in the modelled mode considering all factors.
If error in energy consumption values is intended to work out, simply k9 is substituted by the parameter k10.
As seen above, the lowest amount of deviation takes place in presented model. This error is also low, when only historical data of load and consumption are used, and exclusion of any of the factors increases the deviation substantially.

CONCLUSIONS

Long term load forecasting which has a great deal of influence on investments in distribution, and even on tariff making and pricing of electricity, depends on numerous physical factors. Measures to be taken for development in future, as well as tariff improvement, can be foreseen through identification and forecast of load influencing factors. Alternatively, an optimum state can be established for economic sustainability of electricity distribution industry through orientation of the influencing factors.
As development of distribution network takes place along with urban development culminating in social services, determining network distribution planning would be through the long term load forecasting method introduced in this paper. Moreover, by this method, parameters which exert an impact on load forecasting can be controlled so that the marginal costs of future developments are reduced.
As shown, comprehensiveness of factors and availability of a minimal data period is of utmost importance in reduction of errors in load forecasting.

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