A Reduced Load Model Based on Clustering Concept for Adequacy Evaluation in Power Systems

R. Çağlar
caglar@elk.itu.edu.tr

A. Özdemir
ozdemir@elk.itu.edu.tr

Istanbul Technical University
Electrical and Electronics Faculty
80626 Maslak, İstanbul, TURKEY

ABSTRACT

This paper presents a reduced load model, which can be effectively used in the analysis of electric power systems, especially for the calculation of the adequacy indices of a power system. This reduced load model is obtained using a reduction algorithm based on clustering concept. The clusters have been formed according to relative orders among the load values. Clusters have two main parameters: the cluster seed and the number of cluster members. Reduced load model can be depicted using these parameters. In addition, algorithms for simplifying load probability and frequency calculation are described. These algorithms provide substantial reductions in computational time requirement. Accuracy of the results obtained using this algorithm is sensitive to the number of clusters. Finally, the proposed load models are obtained for the RTS-24 bus system.

Keywords: Load Modeling, Clustering, Cluster Seed, Reduction Algorithm, Adequacy Indices.

1. INTRODUCTION

The basic function of a power system is to meet to the customers' load demands as economically as possible and with an acceptable degree of reliability and quality. The load demand in a power system in any time period (a year, a month, a season, a week, a day or an hour) is a stochastic process, which is difficult to describe with a simple mathematical formula [1]. Depending upon the objective of the analysis, different load models can be established from primary load data.

The load model is one of the most important tools in the analysis of electric power systems. It has been used for various purposes, such as [2]:

- Estimating the operating cost of a power system,
- Predicting the amount of energy delivered by each unit,
- Calculating reliability indices [1,3],
- Forecasting long-term and short-term loads [4,5],
- Demand side management [6]
- Conducting stability studies [7].

This paper is focused on developing a reduced load model for the power system adequacy evaluation. The adequacy is one of the two basic aspects of reliability evaluation of a power system. The other is system security [3,8]. Adequacy indices can be computed both for the generating system planning and composite system planning. The most important indices are Loss of Load Expectation (LOLE), the Expected Energy Not Served, and Frequency & Duration of failure states.

All the reliability indices mentioned above are considerably affected by the system load characteristic and by the adequacy of the load modeling. For this reason load modeling is one of the major tasks in adequacy evaluation. It is easy to form appropriate risk models for generating capacity reliability evaluation due to the direct convolution of generation and load models. Risk model formation for composite system reliability evaluation possesses several difficulties since it necessitates transmission constraints and a different load model at each load bus. In addition, there are many complications, such as overload effects, voltages violations, redispatch of generation and the independent, dependent, common cause and station-associated outages. Due to the large number of states required for a reasonable evaluation, appropriate reduction techniques are necessary for saving computation time. Reduced load model algorithm is one of these reduction techniques [9,10]. Reduced load model can be used either for an entire system or for a single load bus evaluation.

One suitable approach to obtain reduced load model is to use clustering algorithms. Application of these algorithms for single and multiple area load modeling are reported in Ref. [11]. These clustering techniques are based on a process called nearest centroid sorting algorithm.

This paper presents a new clustering algorithm that makes use of the distances of load values. Non-sequential load values are used, since the model is constructed for adequacy evaluation. Load values are arranged from the highest to lowest load values. Taking equal steps from the lowest to the highest load values chooses initial clusters seed or initial values of cluster means. Cluster seeds are continuously updated during the clustering process, so that all clusters are stable.

The proposed load models are obtained for the RTS-24 bus system [12].

2. LOAD MODELS

There are a number of possible load models, which can be used. The required load model can be constructed from primary load data. Normally primary load data include:

1. The maximum weekly load or monthly load in a year.
2. The load in 24 hours in a typical day in each season.
3. The maximum load in each day in a week.
4. The maximum load in each hour in a day.

One of the most widely used models is Load Duration Curve (LDC) in which the individual hourly load values are used. The model assumes the hourly load to be fixed to its maximum value during an hour. The LDC is defined as showing the amount of time that any given overall load level is exceeded. By its definition the LDC is a function whose abscissa specifies the number of hour, in a given period, usually a year, during which customers' demand for power equal or exceeds the associated demand level on the ordinate [2]. That is, the maximum hourly loads during a time period are arranged in a descending order regardless of the time sequence of the given time period.

One of the other most common load models is the one where all the days are represented by their peak loads. The individual daily peak loads can be arranged in descending order to form a cumulative load model, which is known as the Daily Peak Load Variation Curve (DPLVC). Load duration curve and daily peak load variation curve for IEEE 24-bus Reliability Test System (RTS) are given in Fig.1 and Fig.2, respectively. The curve are constructed from the data given in Ref.[12].

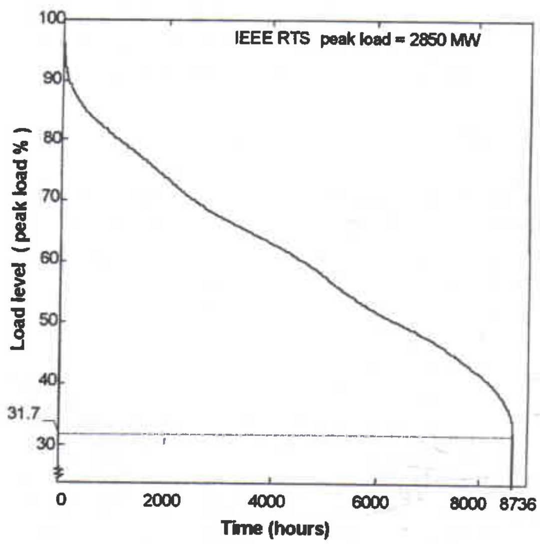

Figure 1 IEEE RTS Load Duration Curve (LDC)

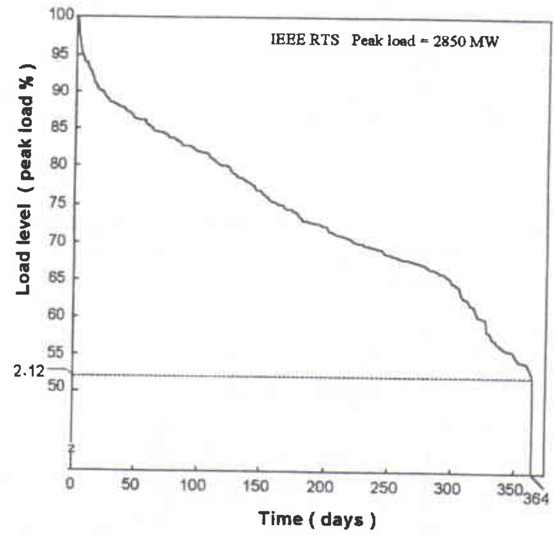

Figure 2 IEEE RTS Daily Peak Load Variation Curve (DPLVC)

3. CLUSTERING OF THE LOAD DATA

One of the methods developed to decrease the computation time is the load clustering, which brings the possibility of dealing with a decreased number of data. Clustering algorithm can be used both the hourly load data and daily peak load data.

Clustering studies have been conducted so far, and the application of these algorithms for single and multiple area load modeling are reported in reference [11]. Starting with hourly load values, a choice of number of clusters, and initial cluster seeds (means), the algorithm performs a disjoint cluster analysis on the basis of Euclidean distances from each hourly observation to different cluster means. This process is called nearest centroid sorting algorithm [11]. The method proposed by [11] has the main disadvantage of determination the cluster components and the cluster mean by processing all the load data all the time. This leads to a considerably time consumption in case of much data. Since sorted (or arranged) load data are generally used in reliability analysis, initial data arrangement worth to be considered deeply. Mean value determination based on initial data arrangement and a consequent data processing provide a considerably time saving.

In this study, data clustering is achieved by using their distances from cluster means. The cluster means are continuously updated due to the number of cluster elements so thus the distances between the cluster means. It is denoted that the data belonging to the clusters and the boundary of each cluster varies during the process, so that all clusters are stable, i.e. there is no change in the clusters membership. The proposed clustering algorithm can be described in the following way.

Let

ny: number of hours or days in the period of study.
nc: number of clusters in the model.
MEAN_i : mean value of cluster i.

Steps:

(a) Sort load data descending order according to their magnitudes regardless time sequences in a given time period.

$$L_D = \left\{ l_1, \ldots l_k, l_{k+1}, \ldots . l_{ny} \right\},$$
$$l_k < l_{k+1}, \quad k = 1,2, \ldots ny-1,$$

where,
l_k : k th load value,
L_D : A set of sorted load values.

(b) Choose the initial values of the cluster means and assign them to MEAN. Taking equal steps from the lowest to the highest load value chooses initial cluster means.

$\mathrm{Inc} = (ny\text{-}1) / nc$, only for the initial step

$\mathrm{MEAN}_i = l_1 + (i-1)\cdot \mathrm{Inc}, \quad i = 1,2,\ldots,nc$

where,
Inc is an incremental value.

(c) Determine the initial boundaries of the clusters.
- For the first and last clusters:

$\mathrm{bnd}_1^{(-)} = l_1, \quad \mathrm{bnd}_1^{(+)} = l_1 + (\mathrm{Inc}/2),$

$\mathrm{bnd}_{nc}^{(-)} = l_{nc} - (\mathrm{Inc}/2), \quad \mathrm{bnd}_{nc}^{(+)} = l_{nc},$

- For the other clusters:

$\mathrm{bnd}_i^{(-)} = \mathrm{MEAN}_i - (\mathrm{Inc}/2),$

$\mathrm{bnd}_i^{(+)} = \mathrm{MEAN}_i + (\mathrm{Inc}/2),$

$i = 2,3,\ldots,nc-1$

where,
$\mathrm{bnd}_i^{(-)}$ and $\mathrm{bnd}_i^{(+)}$ are the down and up boundaries of the i th cluster respectively.

(d) Determine cluster elements for all load data using the following condition. To avoid some process repeating, keep the information of the index of the load data. Take each data in sequence using this information.

If
$\mathrm{bnd}_k^{(-)} < l_i \leq \mathrm{bnd}_k^{(+)}$

then

$l_i \in Cluster_k$

(e) Update Clusters means.

$$\mathrm{MEAN}_k = \sum_{Cluster\ k} \frac{l_{ik}}{noc_k} \tag{1}$$

where,
l_{ik} shows data that belong to Cluster $_k$
noc_k shows the number of data that belong to the Cluster $_k$.

(f) Update incremental values and boundary values of clusters using new cluster means.

$$\mathrm{Inc}_i = \mathrm{MEAN}_{i+1} - \mathrm{MEAN}_i, \tag{2}$$
$$\mathrm{bnd}_i^{(-)} = \mathrm{MEAN}_i - (\mathrm{Inc}_i / 2), \tag{3}$$
$$\mathrm{bnd}_i^{(+)} = \mathrm{MEAN}_i + (\mathrm{Inc}_{i+1} / 2), \tag{4}$$
$$i = 1,2,3,\ldots,nc-1$$

(g) Repeat the step d, e and f until convergence is achieved, that is, there is no change in cluster membership.

(h) After convergence is achieved, values of load for each load state are given by cluster means,

$$l_k = \mathrm{MEAN}_k \tag{5}$$

and probability and frequency are computed by

$$P(L = l_k) = \frac{noc_k}{ny} \tag{6}$$
$$F(l_i \rightarrow l_k) = nlc_{ik} \tag{7}$$

where,
nlc_{ik} is the number of times a change in hourly (or daily) load caused a change in a cluster membership from cluster i to cluster k.

4. SAMPLE SYSTEM STUDIES

In order to test the performance of proposed clustering algorithm, a computer program has been developed. The program forms the reduced load model using hourly load data or daily peak load data over a year. The proposed load models are obtained for the RTS-24 bus system [12]. Load data are clustered a number of clusters, but here we give only two reduced models. One of them has 37 clusters and the other has 103 clusters, and both models use daily peak load data. The Fig.3 shows the reduced load model having 37 cluster seeds. The individual and cumulative load probabilities, and load duration of this reduced load model given in Table I. In addition, the algorithm given at ref.[11] is programmed in order to compare the models. Fig.4 and Fig.5 show the reduced load models obtained from the algorithm given at ref.[11] and from our proposed algorithm respectively.

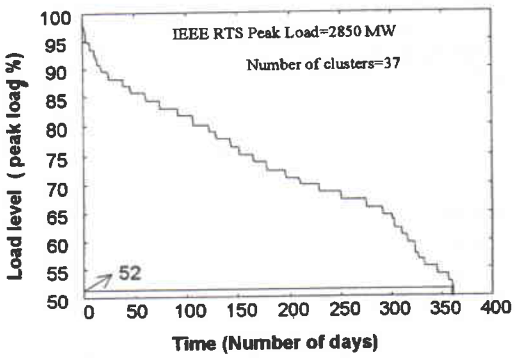

Figure 3 Daily peak load variation curve after clustering daily peak load values into 37 clusters.

TABLE I – PROBABILITIES FOR REDUCED LOAD MODEL

Peak Load level (%)	Individual probability	Cumulative probability	Load duration (day)
100.00	0.0027	0.0027	1
97.50	0.0055	0.0082	2
96.00	0.0027	0.0110	1
94.82	0.0082	0.0192	3
93.48	0.0137	0.0330	5
92.22	0.0055	0.0385	2
90.98	0.0110	0.0495	4
89.80	0.0192	0.0687	7
88.27	0.0385	0.1071	14
87.17	0.0192	0.1264	7
85.94	0.0412	0.1676	15
84.43	0.0385	0.2060	14
83.17	0.0467	0.2527	17
81.98	0.0412	0.2940	15
80.41	0.0440	0.3379	16
79.28	0.0165	0.3544	6
78.03	0.0412	0.3956	15
76.71	0.0220	0.4176	8
75.34	0.0385	0.4560	14
74.20	0.0357	0.4918	13
72.65	0.0522	0.5440	19
71.41	0.0385	0.5824	14
70.26	0.0522	0.6346	19
69.03	0.0577	0.6923	21
67.68	0.0714	0.7637	26
66.30	0.0440	0.8077	16
64.96	0.0247	0.8324	9
64.16	0.0082	0.8407	3
62.59	0.0192	0.8599	7
61.42	0.0165	0.8764	6
60.05	0.0192	0.8956	7
58.22	0.0110	0.9066	4
57.20	0.0137	0.9203	5
55.93	0.0357	0.9560	13
54.48	0.0302	0.9863	11
53.20	0.0110	0.9973	4
52.12	0.0027	1.0000	1

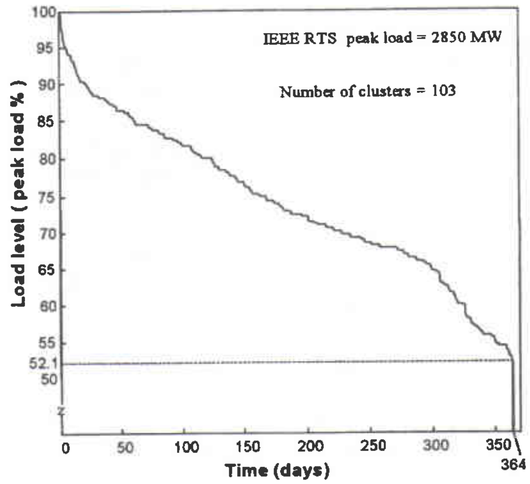

Fig. 4 A reduced DPLVC of IEEE RTS –24 bus using the algorithm given at[11].

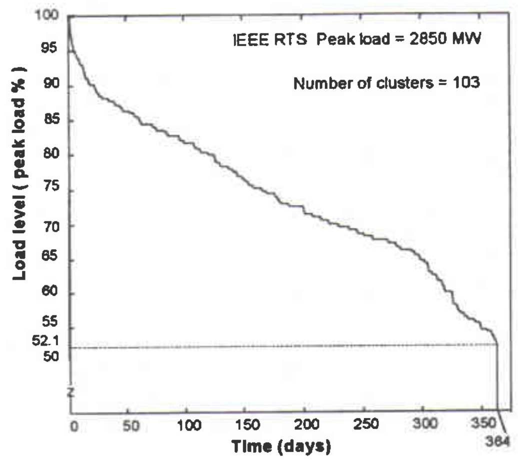

Fig. 5 A reduced DPLVC of IEEE RTS –24 bus using the proposed clustering algorithm.

5. CONCLUSIONS

The algorithm for reduced load modeling has been described. The algorithm is based on clustering concept. The clusters have been established according to the relative orders among the load data. Clusters have to main parameters: the cluster mean and the number of cluster member. The individual and cumulative load probabilities are given using these two parameters. Since sorted load data are used in the algorithm, mean value determination based on initial data arrangement and a consequent data processing provide a considerably time saving.

Accuracy of the results obtained using these algorithms is sensitive to the number of the cluster and initial clusters mean.

The examination of Fig.4 and Fig..5, one can immediately conclude that the proposed method is as effective as the reported in ref.[11]. Therefore, they can effectively be used to obtain reduced load model.

In the proposed clustering process, the data, which have the middle value between two clusters, are assigned to the cluster that possess higher mean value. This situation results in a little fault in the model, however, it can be applicable in reliability evaluation, because there is an agreement with the view of choosing the peak load to a certain extent.

6. REFERENCES

[1] Wang, X., McDonald, J.R., "Modern Power System Planning, McGraw-Hill Book Company, London, New York, 1994

[2] J. Vardi and Benjamin Avi-Itzhak,. "Electric Energy Generation Economics, Reliability, and Rates" The MIT Press, Massachusetts Institude of Technology, Cambrige,Massachusetts, and London, England, 1981

[3] R. Billinton, R.N. Allan, Reliability Evaluation of Power Systems, Pitman Advanced Publishing Program, Pitman Publishing Limited, 1984, London, Great Britain

[4] T. Haida, S. Muto. "Regression Based Peak Load Forecaasting Using a Transformation Technique" IEEE Transactions on Power Systems, Vol. 4, No.1, pp. 1788-1794, November 1994.

[5] H. Yoo, R.L.Pimmel, "Short term load forecasting using a self-supervised adaptive neural network" IEEE Transactions on Power Systems, Vol. 14, No.2, pp. 779-784, May 1999.

[6] S. Rahman, Rinaldy, "An Efficient Load Model for Analyzing Deman Side Management" IEEE Transactions on Power Systems, Vol. 8, No.3, pp. 1219-1226, August 1993.

[7] Wei-Jen Lee, Mo-Shing Chen, U.B.Williams, "Load Model for Stability Studies" IEEE Transactions on Industry Application, Vol.IA-23, No.1, pp.159-165, January-February 1987.

[8] R. Çağlar, "Contingency Selection for The Reliability Evaluation in Electric Power Systems", Ph.D. Dissertation, Institute of Science and Technology, Istanbul Technical University, Turkey, May 1999.

[9] R. Çağlar, A. Özdemir, "Composite Electric Power System Adequacy Evaluation via Transmission Losses Based Contingency Selection Algorithm" IEEE Power Tech'99 Conference, Paper BPT99443-13, Abstract Records page 84, Budapest, Hungary, (Aug 29- Sept 2, 1999).

[10] M.J.Beshir, T.C. Cheng (F) and A.S.A.Farag (M), "Comparison of Two Bulk Power Adequacy Assessment Programs: TRELSS and COMREL" IEEE/PES Transmission and Distribution Conference'96 Proceedings, pp. 431-437, Sept. 15-20, 1996, Los Angeles.

[11] C. Singh, A. Lago-Gonzales, "Improved Algorithm for Multy-Area Reliability Evaluation Using the Decomposition-Simulation Approach" IEEE Transactions on Power Systems, Vol. 4, No.1, February 1989.

[12] Reliability Test System Task Force of APM Subcommittee, "IEEE Reliability Test System", IEEE transactions on Power Apparatus Systems, Vol. PAS-98, No. 6, Nov./Dec. 1979, pp. 2047-2045.

7. BIOGRAPHIES

Ramazan Çağlar was born in Çemişgezek, Turkey, on March 1959. He received his B.Sc., M.Sc. and Ph.D. degrees in electrical engineering from Istanbul Technical University, Istanbul, Turkey in 1983, 1987 and 1999, respectively. His research interests are reliability of electric power system, power system modeling and analysis, distribution system control, fault diagnosis and risk management. Ramazan Çağlar is a student member of IEEE and a member of National Chamber of Turkish Electrical Engineers. Contact address: Istanbul Technical University, Department of Electrical Engineering, 80626 Maslak - Istanbul, Türkiye.

Aydoğan Özdemir was born in Artvin, Turkey, on January 1957. He received the B.Sc., M.Sc. and Ph.D. degrees in electrical engineering from Istanbul Technical University, Istanbul, Turkey in 1980, 1982 and 1990, respectively. He is an associate professor at the same University. His current research interest are in the area of electric power system with emphasis on reliability analysis, modern tools (neural networks, fuzzy logic, genetic algorithms etc.) for power system modeling, analysis and control and high-voltage engineering. He is a member of National Chamber of Turkish Electrical Engineers. Contact address: Istanbul Technical University, Department of Electrical Engineering, 80626 Maslak - Istanbul, Türkiye.