# END USER LOAD PROFILE ANALYSIS FOR DISTRIBUTION SYSTEM PLANNING

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## *ABSTRACT*

*This paper describes the statistical analysis of end user load profile for distribution system planning. Load profiles of aggregate loads from residential, commercial and industrial class are analyzed to determine comprehensive load indices such as load factor, coincident factor, etc. using statistical methods. Additionally, average capacity factor of distribution transformers and probability distribution function of its peak demand with respect to the transformer capacity are also determined in the study. Results of the analysis provide useful inputs for more effective distribution planning.*

## 1.0 INTRODUCTION

Today's projections of electricity demand are uncertain because of changes in population, economy, and even weather conditions. Load profiles are useful input for the planning, design and operation of any distribution system as optimization of financial resources could be achieved through relevant information derived from load profiles. While it is good to have a comprehensive database of load profiles, there should be a thorough attempt to analyze these data to obtain some meaningful load indices for more effective distribution network planning. In addition, load profiles could never be determined with certainty, which means that they should be represented by probability distribution.

In this study by TNB Research (research arm of Tenaga Nasional Berhad) in collaboration with Universiti Tenaga Nasional, load profiles of aggregate loads from residential and commercial class, in different areas are analyzed to determine comprehensive load indices using statistical methods. Additionally, statistical analysis is also performed to establish the probability distribution functions associated with aggregate residential and commercial type loads.

Early approaches in load profiling include load modeling based on analysis of previous data and also prediction of model based on periodicity and weather effect [2-4]. Work has also been carried out in [5] where a model of residential load is developed, taking into account of physiological factors of the consumers using the equipment. In current time, the determination of techniques for load prediction (TLP) by researches can be classified to two main categories. In the first category, the consumers are pre-defined such as residential, industrial, etc. and load measurements are used to determine the TLP of the pre-defined consumers [1, 6-9]. These values are then used to form daily load curve of consumers. Various statistical methods are then used to determine the TLP of a predefined consumer. This method has been widely used in Taiwan [6, 8-9]. The disadvantages of these methods are longer time consumption and some of the probabilistic methods only use some general points of the profile: minimal, maximal, and average power demand of the representative day.

The next category involves grouping the consumers based on the load profile curves obtained. In [10-13], pattern recognition methods have been used to group the customers based on their load curves. These methods however do not indicate a clear way of developing the TLP for a specific group [14]. As a result various clustering techniques were developed to perform the clustering of the groups namely Hierarchical, K-means, Fuzzy K-means, Follow the Leader and Fuzzy Relation clustering techniques [15-18]. Advances in this area include the use of artificial intelligence, e.g. neural networks to develop a clear and less time consuming methodology that is able to form clear and representative group of eligible consumers with appropriate TLPs [14, 19-20].There are also advances in obtaining the load curves, which is utilization of Graphical Information System (GIS) and SCADA and integrating it with customer metering and billing data to obtain a more accurate load modelling [20].

## 2. AGGREGATE LOAD PROFILES AT DISTRIBUTION TRANSFORMERS

In this study, latest load profiles of aggregate customer loads are obtained from 24 hour measurement at 480 distribution substations in the three areas, namely Shah Alam, Subang Jaya and Bangi. Power recorded at the lower voltage (LV) of distribution transformers are sum of power consumed by large number of a variety of loads. Hence, the 24 hour load profiles characteristics are dependent on the types of electricity consumers supplied through the particular distribution transformer.

Based on the measurement, load profiles for residential, commercial and small-scaled industrial customers are generically represented in Figure 1(a), Figure 1(b) and Figure 1(c) respectively.

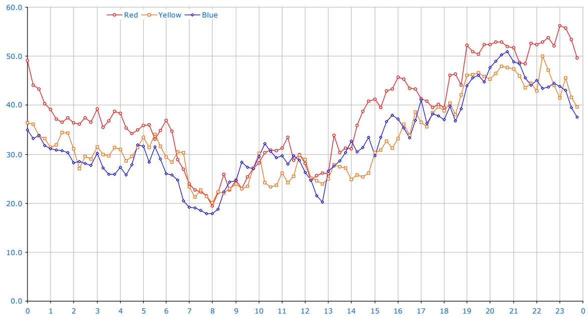

Figure 1(a): Residential Aggregate Loads

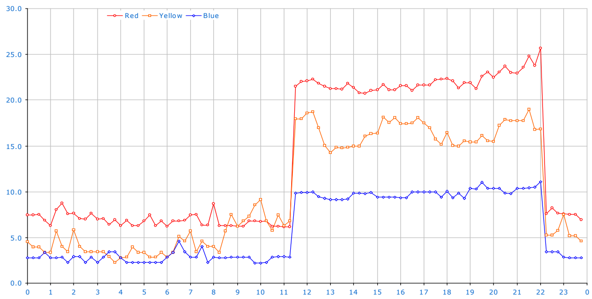

Figure 1(b): Commercial Aggregate Loads

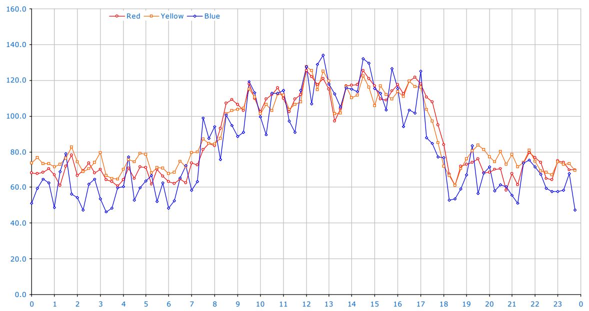

Figure 1(c): Small-scaled Industrial Aggregate Loads

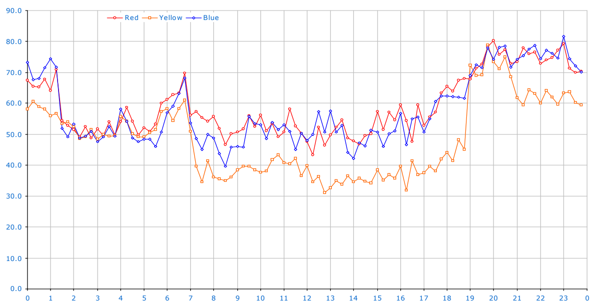

Figure 1(d): Mix Residential and Commercial Aggregate Loads

Based on the above figures, the load profiles for residential, commercial and small-scaled industries are quite predictive in terms of peak demand periods. In cases where substations feed mixed types of loads i.e. combination of residential and commercial/industrial loads, the profiles usually show two peak demand periods, one during the day and another during the night, or otherwise a more flattened load profile throughout the 24 hour period, as shown in Figure 1(d).

## 3. STATISTICAL ANALYSIS OF LOAD PROFILES MEASURED AT DISTRIBUTION TRANSFORMERS

Normalized load shapes are established to compare the variations between each load curves and to calculate average load factors and coincident factors.

### 3.1 Load Factors of Aggregate Loads

Load factor is an expression of how much energy was used in a time period, versus how much energy would have been used, if the power had been left on during a period of peak demand. It is a useful indicator for describing the consumption characteristics of electricity over a period of time. Basic formula for load factor is the average power divided by the peak power, over a period of time [1, 6].

Load factors of aggregate loads taken at distribution substations are statistically determined and summarised in Table 1.

Table 1: Load Factors of Aggregate Loads Taken at Distribution Substations

| | Bangi | Shah Alam | Subang Jaya | |
|---|---|---|---|---|
| **Load Type** | **Average LF** | **Average LF** | **Average LF** | **Average** |
| **Residential** | 0.62 | 0.66 | 0.64 | 0.64 |
| **Commercial** | 0.61 | 0.52 | 0.50 | 0.54 |
| **Industrial** | 0.73 | 0.74 | 0.65 | 0.71 |
| **Mix** | 0.64 | 0.51 | 0.62 | 0.59 |

From Table 1, average group load factors for residential, commercial and industrial customers are 0.64, 0.54 and 0.71 respectively. The figures show slight increase as compared to previous year's measurements. It is therefore recommended to apply updated load factors at the planning stage of distribution system for the respective areas.

### 3.2 Coincident Factors (CF)

Generally, peak demands shown in load profiles do not coincide at the exactly the same time. Hence, the total peak demand of a group of customer loads is the sum of individual customer peak demand multiplies by a factor of less than 1.0 as described in the following formula [7, 9]:

$$CF = \frac{\text{observed peak for the group}}{\sum \text{individual peaks}}$$

Where, CF = Coincident factors

Table 2: Coincident Factors Based On Mixed Customer Load Types in Shah Alam

| Shah Alam | | | |
|---|---|---|---|
| Residential (%) | Commercial (%) | Industrial (%) | Coincident Factor |
| 100 | 0 | 0 | 0.873 |
| 0 | 100 | 0 | 0.758 |
| 0 | 0 | 100 | 0.730 |
| 70 | 30 | 0 | 0.777 |
| 70 | 0 | 30 | 0.825 |
| 30 | 70 | 0 | 0.713 |
| 0 | 70 | 30 | 0.710 |
| 0 | 30 | 70 | 0.665 |
| 30 | 0 | 70 | 0.766 |
| 40 | 30 | 30 | 0.726 |
| 30 | 40 | 30 | 0.693 |
| 30 | 30 | 40 | 0.710 |

Based on load profiles taken from distribution transformers at Shah Alam, Bangi and Subang Jaya, their respective coincident factor is computed. Sample results for Shah Alam area is shown in Table 2. For Bangi and Subang Jaya areas, the coincident factor ranges from 0.65 to 0.9, depending on the load compositions.

### 3.3 Capacity Factor of Distribution Transformers

Capacity factor is defined as the ratio between peak demands of the transformer against its rated capacity. Average capacitor factor of distribution transformers for the three areas are calculated and tabulated in Table 3.

Table 3: Average Capacity Factor of Distribution Transformers

| Area | Average Capacity Factor (%) |
|---|---|
| Shah Alam | 26% |
| Subang Jaya | 39% |
| Bangi | 38% |

The three areas where the load profiles were obtained are generally matured areas of development. Findings of this study show that a high proportion of distribution transformers are operating with a capacity factor of less than 40%, in particular 750 kVA and 1000 kVA transformers.

## 4. PROBABILISTIC DISTRIBUTION OF PEAK DEMAND AT DISTRIBUTION TRANSFORMER

Statistically aggregate power demands at the distribution substations are probabilistic in nature. This has been confirmed by the measurements and load profiles, which means that they should be represented by probability distribution curves. In the study, samples of load profiles from distribution transformers feeding residential and commercial loads for the three areas are analyzed to establish its peak demand statistical distribution with respect to the transformer capacity. The following steps describe the approach used:

Step 1: Identify and select samples of load profiles based on residential and commercial load type.

Step 2: Group the residential and commercial load profiles according to the transformer capacity, for example, load profiles of 750 KVA distribution transformers, etc.

Step 3: Extract the peak demand from each load profile according to the distribution transformer capacity grouping and load types. For example, under 750 kVA transformer and residential load group, the peak demands are $\{x_1, x_2, \ldots\ldots x_n\}$ kVA, where $n$ is the number of load profiles.

Step 4: Establish the normalized probability distribution function of the peak demand as in step 3.

Results of the statistical analysis for 1000 kVA transformers feeding residential loads and commercial loads are shown in Figure 2 and Figure 3 respectively.

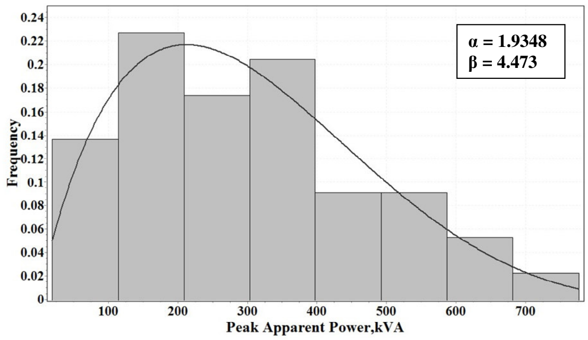


Figure 2: Probability Distribution of Peak Demand of 1000 kVA Transformers Feeding Residential Loads

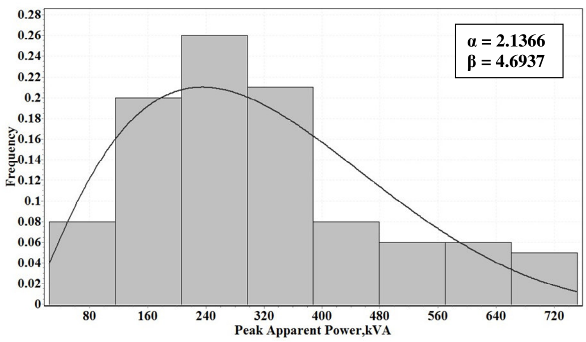


Figure 3: Probability Distribution of Peak Demand of 1000 kVA Transformers Feeding Commercial Loads

Results of the statistical analysis indicate that the probability distribution curve of power demand at 1000kVA distribution transformers tends to follow the beta distribution function, which is skewed to the left. The same pattern also applies for 500kVA and 750kVA transformers. Considering that the three areas have reached matured development status, there is plenty of excess capacity for any load growth. A more optimal approach in sizing distribution transformers could be achieved based on the parameters of the beta distribution.

## 5. CONCLUSION

The study is generally successful in providing insight and understanding of consumer usage of electricity, in terms of its load factor, coincident factor and statistical distribution of peak demand against equipment capacity. The analysis shows that on average, there are overcapacities of distribution transformers as well as a likelihood of overestimating the transformer capacity at planning stage. In addition, probability distribution curve of power demand tends to follow the beta distribution function. A more optimal approach in sizing distribution transformers could be achieved based on the parameters of the beta distribution. Updated load indices shall also be used at the planning stage of distribution system for respective areas. With a clear understanding of electricity usage pattern by consumers, a more optimal investment plan for distribution network could results in substantial savings for the utility.

## Acknowledgments

An acknowledgement is made to Distribution Division of TNB for their support, valuable inputs and assists especially in data collection. Special mention also goes to all UNITEN team members involved in completing the research project.

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