

Residential Load Models for Network Planning Purposes

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Abstract— Network planning is a major task for every electric utility and the major goal is to comply with the loading capacity of the equipment and to provide the desired voltage to the customer. The difficulty is to model the customers demand and the loading of the equipment. A worst-case scenario coupled with an estimation of the load increase for the planning horizon is a typical engineering approach for the dimensioning of the network. Especially for low-voltage network planning little is known about the residential loads. One characteristic of these loads is the diversity and stochastic. The networks do not have to withstand the worst possible combination of demands. The effect of diversity changes with the number of customers and evens out. The coincidence factor takes account for this behavior calculating the demand of several customers. In this paper the characteristics of residential loads are shown and several options for the determination of the maximum load are explained and compared. This includes the coincidence factor, Velander's formula, the Herman-Beta method and the bottom-up approach.

Keywords: power distribution planning, load modeling, bottom-up load model, stochastic load model, coincidence factor

I. INTRODUCTION

The role of the power supply industry is changing in various ways. In many countries the regulation requires a more cost-conscious operation and planning of power systems. Often the classic utility companies had to be split because of monopoly reasons (unbundling) and to boost competition in sectors such as generation, sales and measurement. These changes may result to less information for the network planning process.

Further changes include the advancement in the information and communication technology. This makes it possible to gather information from the assets as well as from the customers. With the introduction and advancements of geographic information systems (GIS) the designing process of low-voltage networks is also changing. Much more information about the equipment is available as well as tools for load flow analysis are established. To perform these calculations reliable load models are required. Most models are designed for a worst-case calculation, considering the time of maximum demand and minimum supply on the one hand side as well as minimum demand and maximum supply contrariwise.

To understand the load models the behavior of residential loads has to be studied. The diversity of residential loads is known and implemented in every planning process. The

diversity describes the fact that an ordinary customer has a constant base load of some hundred watts and seldom peak loads of some kilowatts. The peak loads of several customers occur rarely at the same time and therefore the coincident peak demand is introduced. The coincident peak demand represents the maximum demand for a group of customers during periods of peak system demand. This is reasonable since the equipment in a network has to withstand different loadings and therefore contributes differently to the voltage drop.

In this paper different load models for the network planning process will be explained. The mixture of residential appliances will be shown and characterized. Two types of load models are explained and modifications are presented. With the first type of load models the influence of customers on the coincident peak demand can be calculated. Only this demand is of interest and no information is given about the duration or the frequency of its occurrence. The second type is the so-called bottom-up approach which is more accurate and results in a load curve. This load curve can be analyzed and used not only for the network planning purposes, but also for network operation.

II. DISTRIBUTION SYSTEM NETWORK PLANNING

The design of low-voltage distribution systems requires a different approach than the design of transmission systems. This is partly due to the lack of measuring systems and data acquisition. Therefore there is no measurement available and the network state is not known for any given specific time.

In the designing process of low-voltage distribution systems characteristics as the (n-1)-criteria are often not relevant and are not considered.

The main technical criteria for the distribution system planning process are voltage-drop, loading capacity of the equipment and short-circuit current. The main economic criteria are capital costs, operating costs as well as costs due to losses.

Within these criteria finding a feasible design is possible. Not knowing the future load and technology changes finding the best design with the lowest costs is impossible.

In the design process the modeling of the equipment such as cables and transformers is very accurate. The load modeling is mostly based on a worst-case of finding the coincident peak demand. With this model the maximum voltage drop and the loading capacity of the equipment can be evaluated. No

information is given about the duration and the probability. The load modeling should be studied intensely with respect to the smart grid and its effect on the planning process [1]. This also includes a better consideration of the load factor. Often a fixed power factor in the range of 0,9 to 1 is assumed while varying the active power or the load current.

Changes in the planning process are also required with the possibility of demand side management or the charging of electric vehicles. To reduce the costs for distribution networks the focus has to be on the load models. With more knowledge of the characteristics of the load and the possibility of modeling loads for future scenarios it will be possible to evaluate network configurations.

III. TYPICAL PATTERN OF RESIDENTIAL LOADS

A typical load curve for a week of one residential customer is shown in fig. 1. It is evident that there is a constant base load especially during night. Additional peaks are seen depending on the activity of the inhabitants of the home. To broaden the understanding of the load pattern a closer look should be done at the household appliances.

A. Classification of Domestic Appliances

Domestic appliances can be classified in several ways. Most equipment can be assigned to brown goods, white goods or small appliances.

1) Brown goods

Relatively light electronic consumer goods are often called brown goods. They can be divided into equipment for office/communication or entertainment. There is no fixed limit between these appliances and their relationship is changing with the fast innovation in this sector

- Office/Communication equipment: PC, LCD, printer, scanner, phone, router, etc.
- Entertainment electronics: TV, CD/DVD player, hi-fi system, video game console, projector, etc.

2) White goods

White goods are also called major appliances or whiteware. They are major domestic appliances accomplishing some routine housekeeping tasks such as cooking, food preservation or cleaning.

- Kitchen appliances: stove, refrigerator, freezer, dishwasher, microwave, etc.
- Laundry appliances: washing machine, laundry dryer, drying cabinet, etc.
- Heating, Ventilation and Air Conditioning (HVAC): air condition, water heater, etc.

3) Small appliances

In comparison to brown and white goods small appliances are portable or semi-portable. Many small appliances are kitchen appliances as well as for personal care.

- Kitchen appliances: kettle, toaster, blender, waffle iron, juicer, coffee machine, etc.

- Household appliances: fan, iron, sewing machine, vacuum cleaner, clock, etc.
- Electronic devices: mobile phone, PDA, digital (video) camera, radio, mp3 player, digital photo frame, netbook, e-book reader, etc.
- Personal care: hair dryer, curling iron, shaver, electric toothbrush, etc.

4) Lighting

The illumination of homes during twilight and night as well as of windowless rooms or workplaces is also an important part of residential energy consumption. Due to energy-saving lamps their effect on power system planning is decreasing.

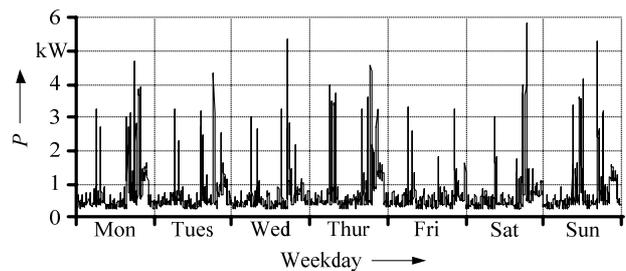


Figure 1. Load curve of a single household for a week

B. Peak demand of domestic appliances and their use

The classification shows a variety of domestic appliances which can be found with a diverse penetration in different homes. Of interest are the appliances with a high penetration. They also have to be often at use or contribute a high peak load. To exemplify the relevance of some appliances fig. 2 shows the load of appliances versus the frequency of use per year of an arbitrary customer.

The use of the appliances and the frequency of use vary depending on the behavior and preferences of the inhabitants. The variation of peak load is due to the fact that appliances have different working points. The washing machine has heating, soaking, centrifuge and pumping cycles. Some appliances, even with a high peak load, can be neglected since they are seldom in use (e.g. waffle iron).

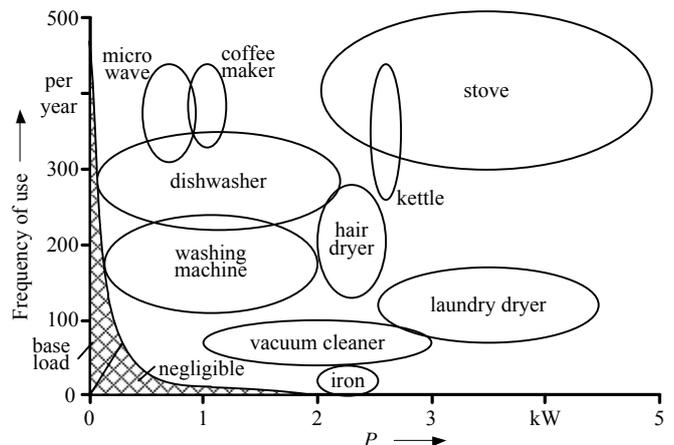


Figure 2. Load versus frequency of use for several appliances

Other appliances are often used but have low power consumption. They can be combined as base load. The refrigerator is not shown in fig. 2, but its impact on the energy consumption of a household is significant and the peak power is between 80 W to 150 W.

C. Classification of Residential Customers

Variations in the consumption are not only due to the preferences of the customer but also to the infrastructure. Table I shows different customer types depending on the electrification of their homes. The term basic means that all domestic appliances except for the electric stove and electric heating for space or water can be used. Partly-electric customers use in addition an electric stove. If electricity is used for heating of water or space it will become the major design criterion in terms of maximum demand and diversity of the load. Water heating is realized with storage systems (e.g. boiler) with small maximum demands or with instantaneous water heaters (flow-type) having a high power rating because of the fast heating of the water when needed. All-electric customers use electricity also for space heating. This is often done with night-storage heaters to use inexpensive energy and the available network capacity during the night hours.

Appliances used with electrical energy may substitute others used with different energy sources. This can increase the residential load and energy consumption. Examples are electrical heat pumps or vehicles using electric motors and batteries for propulsion.

TABLE I. CLASSIFICATION OF RESIDENTIAL CUSTOMERS

Customer type	Appliances in use				
	general	electric stove	storage water heater	flow-type heater	electric space heating
basic	x	-	-	-	-
partly-electric	x	x	-	-	-
fully-electric (boiler)	x	x	x	-	-
fully-electric (flow-type)	x	x	-	x	-
all-electric	x	x	x	-	x

D. Regional Variations of Domestic Load Models

Residential loads are depending on specifics of the country, location of the customer, climate distinction and infrastructure. Some countries make use of electrical energy for heating. This can be due to cheap electrical energy from hydropower plants or the heating demand is relative small and investment in a different energy source for heating is more expensive.

E. Diversity of the Residential Load

The main characteristic of residential loads is the fact that the peak demand is drawn for a short time period at the activity hours of the inhabitants. With an increasing number of customers the coincident demand of a group increases slowly. This fact is known and considered since the electrification of residential areas had started at the end of the 19th century [2], [3].

IV. RESIDENTIAL LOAD MODELS REPRESENTING COINCIDENT PEAK DEMAND

For distribution network planning purposes the worst-case has been of interest. There are several approaches which will be derived.

A. Coincidence Factor

The diversity of the residential load has been considered in the network planning process at a very early stage. Rusck presents a derivation of calculating the effective demand of a group of similar customers [4]. In the paper it is stated that the demand of a residential customer is not normal distributed. The assumption is that the loads of the individual customer during the peak system demand are normal distributed. With this assumption the standard deviation σ_i of a load curve $P_i(t)$ is calculated with the mean load P_0 .

$$\sigma_i = \sqrt{\int (P_i(t) - P_0)^2 dt} \quad (1)$$

Summing up several normally distributed loads will result in a load curve which is also normally distributed. For the standard deviation of the resulting load curve applies

$$\sigma = \sqrt{\sum_{i=1}^n \sigma_i^2}, \quad (2)$$

where σ_i is the standard deviation of the i -th load. The distribution curves of all loads are assumed to be similar in shape. With this assumption Rusck argues that the difference between the maximum value of each load and its mean value is proportional to the standard deviation.

$$P_{\max}(n) - \sum_{i=1}^n P_{0i} = \sqrt{\sum_{i=1}^n (P_{\max i} - P_{0i})^2} \quad (3)$$

In eq. (3) $P_{\max}(n)$ is the coincident peak demand of n customer. With n normally distributed equal loads with the mean load P_0 and the equal maximum demand per customer $P_{\max 1}$ the coincident peak demand is

$$P_{\max}(n) = n \cdot P_0 + (P_{\max 1} - P_0) \cdot \sqrt{n}. \quad (4)$$

Dividing eq. (4) by $P_{\max 1}$ and n gives the coincidence factor c as result. The coincident factor is defined as the coincident peak demand $P_{\max}(n)$ of a group of customers within a specified period to the sum of their individual maximum demands within the same period and can be between 0 and 1.

$$c = \frac{P_{\max}(n)}{n \cdot P_{\max 1}} = \frac{P_0}{P_{\max 1}} + \left(1 - \frac{P_0}{P_{\max 1}}\right) \cdot \frac{1}{\sqrt{n}} \quad (5)$$

$$= c_{\infty} + (1 - c_{\infty}) \cdot n^{-1/2}$$

For eq. (5) it is assumed that all customers have the same maximum demand or an average maximum demand per customer can be applied. A variety of formulas for calculating the coincidence factor has been published on empirical studies. Nickel and Braunstein [5] found with eq. (6) a curve by evaluating several curves published in the United States.

$$c = 0,5 \cdot \left(1 + \frac{5}{2n+3}\right) \quad (6)$$

With eq. (7) the coincident peak demand of a group of similar customers can be calculated in an easy way.

$$P_{\max}(n) = n \cdot c \cdot P_{\max 1} \quad (7)$$

Fig. 3 shows the drop of peak load contribution to the coincident peak demand as the number of customer increases. For 50 customers and $c_{\infty} = 0,1$ the coincident peak demand is 114 kW and each customer contributes 2,3 kW to this demand. In this example it is assumed that the maximum demand per customer $P_{\max 1}$ is 10 kW. The graph also includes the coincidence factor according to Nickel and Braunstein. The declining of the curve is small compared to the others. This can be due to the use of air-conditioning which have a heavy influence on the residential load because of a little diversity.

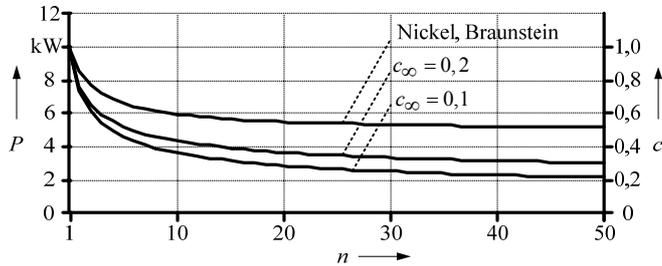


Figure 3. Peak load contribution per customer as a function of number of customer with the corresponding coincidence factor on the right axis

The calculation of the coincident peak demand depends on the customer type. Possible values for c_{∞} and the maximum demand per customer are given in table II. The factor c_{∞} is very low for fully electric customers with flow type water heating. This is due the fact that water is heated only if it is needed and the operating time is short. The factor is very high for all-electric customers because all heaters use energy at the same time during the night. This can be reduces by using control equipment. Also a range of results for the coincident peak demand of 100 customers is shown. This presents that the parameters have to be carefully selected and verified.

TABLE II. EXAMPLES FOR MAXIMUM DEMAND PER CUSTOMER AND c_{∞} FOR DIFFERENT CUSTOMER TYPES

Customer type	$P_{\max 1}$ in kW	c_{∞}	$P_{\max}(100)$ in kW
basic	4 ... 6	0,10 ... 0,20	76 ... 168
partly-electric	5 ... 11	0,10 ... 0,15	95 ... 259
fully-electric (boiler)	8 ... 12	0,10 ... 0,20	152 ... 336
fully-electric (flow-type)	30 ... 35	0,05 ... 0,07	435 ... 571
all-electric	25 ... 35	0,70 ... 0,80	1.843 ... 2.580

B. Superimposed Coincidence Factor

The coincidence factor cannot only be applied to similar customer types. Due to the fact that behavior pattern of different customer types still coincide in part allows the use of a superimposed coincidence factor [6] (interkategorialer Gleichzeitigkeitsfaktor). This factor can be applied to calculate the coincident peak demand having different customer types.

C. Diversity Factor

The diversity factor is the reciprocal of the coincidence factor. The diversity factor is therefore larger or equal one. Sometimes the diversity factor and the coincidence factor are mixed up. Rusck introduces a diversity factor now known as coincidence factor.

D. Velander's Formula or Strand-Axelsson Formula

Velander's formula is widely used in Scandinavia and was described by Velander around 1950 [7], [8]. Axelsson and Strand used the formula in a CIRED publication [9] and it also became known as Strand-Axelsson formula. The method is used to transform an annual energies E into maximum demand per customer $P_{\max 1}$.

$$P_{\max 1} = k_1 \cdot E + k_2 \cdot \sqrt{E} \quad (8)$$

The factors k_1 and k_2 are empirical coefficients and examples are given in table III. Also possible maximum demands per customer depending on the annual energy consumption are included. The coincident peak demand is calculated with $c_{\infty} = 0,2$.

The coincidence of n customers can be included into Velander's formula so that the coincident peak demand can be calculated with eq. (9).

$$P_{\max}(n) = n \cdot k_1 \cdot E + k_2 \cdot \sqrt{n \cdot E} \quad (9)$$

$$k_1 = P_{\max 1} \cdot c_{\infty} / E \quad (10)$$

$$k_2 = P_{\max 1} \cdot (1 - c_{\infty}) / \sqrt{E} \quad (11)$$

TABLE III. VALUES FOR VELANDERS FORMULA

Classification	k_1 in h^{-1}	k_2 in (kW/h) $^{-1/2}$	E in kWh	P_{max1} in kW	$P_{max(100)}$ in kW
Domestic [8]	$0,33 \cdot 10^{-3}$	0,05	2.000	2,9	81
			3.500	4,1	115
			5.500	5,2	145
Rural regions [9]	$0,20 \cdot 10^{-3}$	0,10	2.000	4,9	136
			3.500	6,6	185
			5.500	8,1	226
Towns and cities [9]	$0,25 \cdot 10^{-3}$	0,06	2.000	3,2	89
			3.500	4,4	124
			5.000	5,5	154
Domestic [8] with eqn. (9)	$0,33 \cdot 10^{-3}$	0,05	2.000	2,9	88
			3.500	4,1	145
			5.000	5,2	200

The factors k_1 and k_2 can also be calculated with eqn. (10) and (11) [7]. In the last row of table III eq. (9) is deployed to calculate the effective demand of 100 customers using the factors of row 2 (Domestic). This results in different coincident peak demands.

E. Herman-Beta method

A load research program was launched in South Africa with measurements beginning in 1991 [10]. This was necessary because of an electrification program with the goal of providing electricity to a large portion of the population. Instead of considering power, the load current was measured and analyzed. The developed method became known as the Herman-Beta method.

Also the sampling rate of the measurements was investigated by varying the sampling intervals. It is described that a favorable sampling interval would be 5 minutes. The currents for a 10 minutes sampling interval were around 2 % lower because of the average determination whereas the results of the 2 minutes sampling interval were just 1 % higher. Smaller intervals are not appropriate for network planning processes [10] but can be of interest in stability calculations.

It was found that the currents of the customers at the time of the maximum effective demand are best described with a beta probability function. This distribution can be bounded to zero as a minimum and a particular maximum value, e.g. the circuit breaker rating. The significance level was evaluated as low but still regarded as most suitable in comparison to eight different distribution functions [10]. The beta distribution function is parameterized by two positive parameters typically denoted by α and β . The probability density function can be left-skewed for customers whose loads are not restricted or right-skewed for customers whose loads are restricted by a low circuit breaker dimensioning [11]. Values for α and β and their application to network planning are as well described in [12] and in other publications.

The Herman-Beta method was also applied on different customer connection patterns [13]. This allows considerations on the voltage drop as well as voltage unbalance in a network resulting from different load connections.

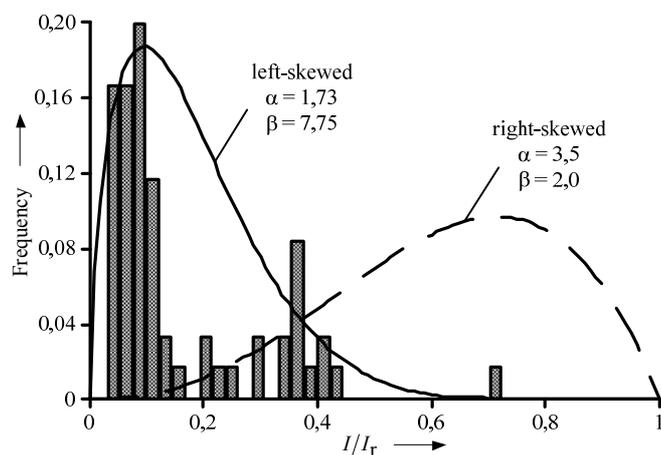


Figure 4. Normalized currents at peak system demand with beta distribution functions

V. RESIDENTIAL LOAD MODEL WITH A BOTTOM-UP APPROACH

The bottom-up approach can be used to model residential demands dependent on the time giving much more information about the characteristics of residential customers. The drawback is the extensive demand for input data which cannot be easily found and includes life-style-related psychological factors [14], [15]. The concept of a bottom-up approach for residential load modeling was also developed by Piller in 1980 which also includes statistical examinations of the customer behaviors [16].

Research was also done on gathering input data for models. Customers can only describe their behavior and lifestyles. These linguistic variables have to be transferred into computerized forms and have to include the uncertainty in terms of linguistic variables [17]. Load models for network planning purposes use load forecastings which cannot be verified using surveys. Therefore assumptions have to be made and different scenarios have to be developed. Knowledge about the influence of appliances and their use is essential. Scenarios could include:

- use of electricity for transportation systems,
- reduction of the energy consumption of white appliances,
- change in the cooking behavior.

The models include different groups of customers depending on the household size, their employment or school attendance and the kind of home (apartment, house).

Also the appliances can be grouped in terms of usage:

- usage independent on customer, e.g. refrigerator,
- usage dependent on customer and independent on weekday, e.g. washing machine,
- usage dependent on customer and weekday, e.g. TV.

The procedure of the load modeling follows in general the diagram in fig. 5. The complexity of the data input can be very immense. The appliance penetration can easily be found or approximated. The gathering of social random factors is very difficult and reasonable assumptions have to be made [18].

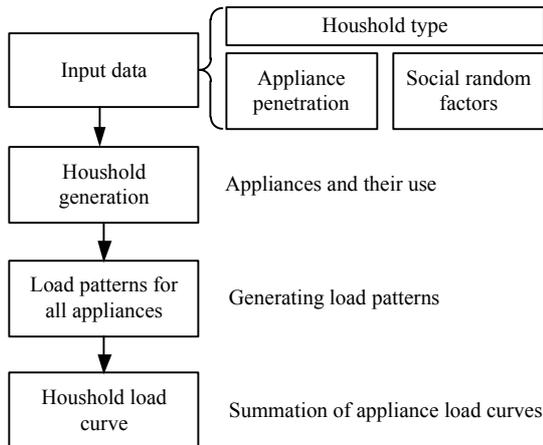


Figure 5. Diagram showing a possible bottom-up load profile generation

The generated load patterns can be verified by comparing results with available measurements. This can include the energy consumptions as well as the coincident peak demand of a large group of customers. A reasonable time interval would be 30 seconds to one minute to generate load patterns of one year. These results can be adjusted by averaging the results to larger time intervals.

The bottom-up approach can also be used for other engineering problems. The influence of demand-side management can be analyzed by varying the use of the appliances [19].

VI. CONCLUSION

Analyzing the demand of residential loads becomes more and more important to find ways to reduce costs of the networks as well as to plan and operate the networks to specified limits. The methods to determine the coincident peak demand worked well in the past but they also have induced an oversizing of the network. Also large load growth scenarios led to oversized networks.

Modeling the individual loads as normal distributed at maximum effective demand is not an appropriate assumption in the designing process. Therefore the formulas by Rusck and Velander are in question. The Herman-Beta method shows that the individual demands at coincident peak demand are not normal distributed. This can also be verified with the bottom-up approach.

A drawback of all load models is the fact that only the total load or the current per phase is considered. Little is known about unsymmetrical load and its effect.

For more accurate calculations the reactive power or power factor has to be considered.

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