

MODERN GRID PLANNING – A PROBABILISTIC APPROACH FOR LOW VOLTAGE NETWORKS FACING NEW CHALLENGES

Thomas WIELAND
TU Graz / IFEA – Austria
t.wieland@tugraz.at

Michael REITER
TU Graz / IFEA – Austria
m.reiter@tugraz.at

Ernst SCHMAUTZER
TU Graz / IFEA – Austria
schmautzer@tugraz.at

Lothar FICKERT
TU Graz / IFEA – Austria
lothar.fickert@tugraz.at

ABSTRACT

In this paper a probabilistic approach for describing, estimating and dimensioning of electrical equipment, such as transformers and low voltage power lines for residential households is compared with the conventionally approach. The new methodology includes residential households, decentralized generating units, electrical storage units and the in the near future expected electric mobility. The performed simulations provide quantiles of probabilistic peak power which are developed by means of simulations considering the distribution functions of different characteristic days (weekday, Saturday, Sunday) and different time periods (winter, summer, transition period) of the measured electrical power consumption from residential households using measured smart meter profiles. A relation between statistical analysis and conventionally coincidence factors is given.

INTRODUCTION

The layout of electrical supply structures and the dimensioning of electrical equipment (e.g. transformers, power lines) in low voltage networks can be done using conventional coincidence factors (VDE [1], TAEV [2], literature [3]) for different usages (office, medium scaled industry, household and industry) or with specific load densities. In general, the planning horizon in electric power engineering for the dimensioning of electrical equipment and electrical installations encompasses 20 years or more. As a result of this procedure the technical planner always risks an unadapt dimensioning. Practical experiences shows the need for a new methodology for the future-proof dimensioning of electrical equipment in the low voltage network due to new challenges e.g. decentralized generation units, high power electric charging stations for electric mobility and decentralized storage units. A new approach is required to allow an effective integration of decentralized sources (decentralized generation units) and loads into a well-adapted energy system.

The regulation in [4] stipulates at least 95 % of Austrian electricity customers have to be equipped with a smart meter by the end of 2019. Therefore the increasing use of information and communication technologies in the low voltage level allows for an in-depth look at consumer habits regarding power consumption for different days and periods of each time step a day.

Analysing this detailed data with real smart meter profiles and the help of statistical methods for residential households of different time periods (winter, summer, transition period) and characteristic days (weekday, Saturday, Sunday) gives new insights and allows, following an overall aim, the comparison between conventional and probabilistic coincidence factors for the dimensioning of electrical equipment (transformers, low voltage power lines).

This paper is structured as follows. Firstly, the method for conventional dimensioning of electrical equipment with coincidence factors is analysed in a comprehensive way. Secondly, a new methodology for generating probabilistic power values is illustrated. This new methodology makes it possible to evaluate the conventional coincidence factors providing a better sense of reality and for generating residential households probabilistic power values considering decentralized generation units, electric mobility and electric storage units. Thirdly, the procedure and the results of the statistical analyses for the recorded load profiles of residential households with the distinction between characteristic days and periods are presented.

Fourthly, the results of the performed simulations between the loads of the residential households together with the decentralized generation units (sources) are shown.

CONVENTIONAL DIMENSIONING OF ELECTRICAL EQUIPMENT

Conventional dimensioning of electrical equipment is undertaken using classical coincidence factors, based on previous experience, listed in standards and regulations (VDE [1], TAEV [2], literature [3]), which do not consider smart grid effects. These coincidence factors $g(n)$ take into account the fact that the electrical appliances of each household don't work parallel at the same time and that the total installed power P_{\max} is not required at the same time. The mathematical relationship is shown in equation (1):

$$g(n) = \frac{P_{S,\max}}{\sum_{i=1}^n P_{\max,i}} \quad (1)$$

As shown in equation (1) the coincidence factor $g(n) \leq 1$. For example the coincidence factor g_{office} for small-scale offices is 0.7–0.5. The coincidence factor of residential households $g_{\text{VDE,max/min}}$ is between 1.0 and 0.1 depending on the number of residential households n_{HH}

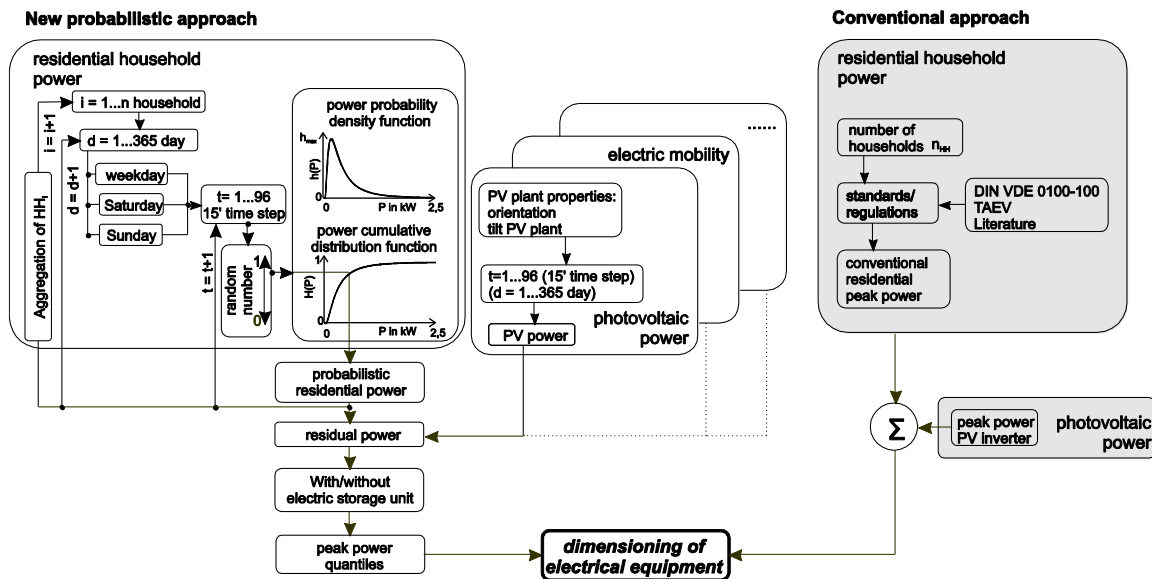


Figure 1 Methodology for the dimensioning of the electrical equipment using power probability density functions for typical days and periods to evaluate peak power quantiles for probabilistic coincidence factors [5]

considered. In the equations (2) the calculation of the maximum peak power $P_{S,VDE,max}$ depending on the number of households n_{HH} is shown.

$$P_{S,VDE,max}(n_{HH}) = P_{HH} \cdot n_{HH} \cdot g_{VDE,max}(n_{HH}) \quad (2)$$

The installed power P_{HH} for one residential household ($n_{HH} = 1$) in Austria is 18 kW (without electric heating). In general, the coincidence factors for the residential households depend on personal-, labour- and leisure-behaviour. These conventional coincidence factors are determined with empiric values as well as load profiles and are used as reference values for the dimensioning of electric equipment. Due to the fact that, in the near future, even more smart meter profiles will be available, these conventional coincidence factors should to be redesigned to determine a possible optimization potential [5].

MODERN GRID PLANING

The conventional electrical grid is planned from high voltage level down to low voltage level. Today, many decentralized generation units are installed in the lower voltage levels, which leads to a bidirectional load flow with atypical power feed-in between protection devices. This means that further investigations regarding peak power and coincidence factors of residential households have to be done in which decentralized generation units are taken into account with a new methodology for the dimensioning of future-proof power systems.

New Methodology

The new methodology for modern grid planning, as shown in Figure 1, takes into account recorded and investigated smart meter profiles of residential households, decentralized generation units and the electric mobility expected in the near future. In the following bottom up approach the sections of the

different relevant input parameters of the new methodology are described.

Residential household – investigated in an Austria urban area

A statistical analysis of recorded smart meter profiles (88 households) allows a detailed investigation of the power consumption of urban residential households in southern parts of Austria.

The time resolution of the recorded smart meter profiles is 15 minutes. The statistical analysis is performed for each time-step for different time periods (winter, summer, transition time) and typical days (weekday, Saturday and Sunday) [5]. According to literature the power consumption of different residential households at a certain time step can be described using a log-normal distribution [7]. This log-normal distribution is depicted in formula (3) and can be described with the shape parameter μ and the scale parameter σ .

$$f(x) = \begin{cases} \frac{1}{\sqrt{2\pi}\sigma x} \cdot e^{-\frac{(\ln(x)-\mu)^2}{2\sigma^2}} & x > 0 \\ 0 & x \leq 0 \end{cases} \quad (3)$$

In order to demonstrate the general behaviour of the log-normal distribution it can be shown that a high value of the shape parameter μ results in a high probability of high power values for the demand. A high value of the scale parameter σ indicates a high dispersion of the expected power values. The output of the carried out statistical analysis regarding the smart meter profiles for many households is the distribution density parameters (log-normal distribution form parameter $\mu(t)$ and shape parameter $\sigma(t)$) of each time step a day (96 values) with a time resolution of 15 minutes for typical days (weekday, Saturday, Sunday) and different time periods (winter,

summer, transition period).

In Figure 2 the form parameters $\mu(t)$ of the winter period (weekday, Saturday, Sunday) for each time step (00:15 – 24:00) are shown.

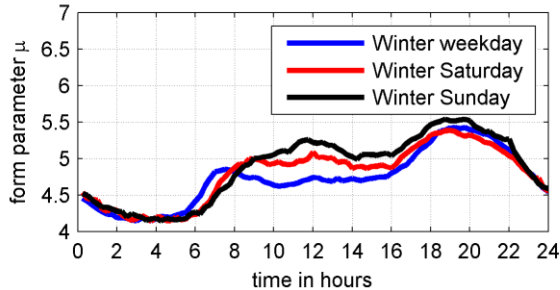


Figure 2 Log-normal distribution – form parameter $\mu(t)$ for winter period (weekday, Saturday, Sunday) [6]

As shown in Figure 2 the form parameter $\mu(t)$ of the log-normal distribution for weekdays compared to the days on the weekend (Saturday, Sunday) is different:

A higher probability for high power values is likely on weekdays in the morning between 05:30–08:00 compared to the days on weekend. During midday there is an obvious difference between weekdays, Saturday and Sunday. This can be explained by the working hours during a week.

Between 18:00–22:00 in the evening, the relative difference between the form parameter $\mu(t)$ for weekdays and Saturday compared to Sunday is about 4%. At this time period the highest power values are expected.

In Figure 3 the shape parameters $\sigma(t)$ during the winter period (weekday, Saturday, Sunday) are shown.

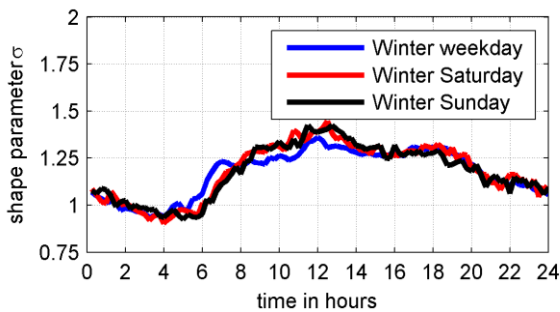


Figure 3 Log-normal distribution – shape parameter $\sigma(t)$ for winter period (weekday, Saturday, Sunday) [6]

In Figure 3 the course of the shape parameters $\sigma(t)$ for Saturday and Sunday are very similar. In general, the shape parameters $\sigma(t)$ are higher during the day than during the night. This results in a higher dispersion of power values during the day.

For weekdays, the shape parameter $\sigma(t)$ show higher values between 06:00–08:00 which is based on a higher dispersion of the measured power consumption. This can be explained by the individual personal behaviour in the morning.

The probabilistic residential power values p_{HH} are based on consumer behaviour and are modelled with the methodology shown in Figure 1. A uniformly distributed

random number (between 0 and 1) is used (see Figure 1) to generate the probabilistic power values p_{HH} for a various different number of households n_{HH} based on the distribution parameters of the log-normal distribution ($\mu(t)$ and $\sigma(t)$) for each time step t .

Decentralized generation units (DG)

To demonstrate the methodological integration of decentralized generation units in this methodology, photovoltaic power plants are used as an example. The dependency of the photovoltaic output power p_{PV} is shown in a very simplified form with the following formula (4) [8]:

$$p_{PV}(G_{Mod}, T, \gamma_E, \alpha_E, A_{Mod}, t) = \eta_{Inv}(G_{Mod}, T(t)) \cdot \eta_{PV}(G_{Mod}, T(t)) \cdot G_{Mod}(\gamma_E, \alpha_E, t) \cdot A_{Mod} \quad (4)$$

The photovoltaic power p_{PV} is highly dependent on the global irradiance G_{Mod} , the ambient temperature T , the mounting angle γ_E , the azimuth angle α_E and the surface area A_{Mod} of the photovoltaic panels.

As a first step a recorded load profile for a whole year from a photovoltaic power plant in the south of Styria, within a 15 minute time step resolution, is used as input.

It is planned to perform further investigations on peak power reduction respectively peak load shift and probabilistic coincidence factors using a different mounting angle γ_E and different orientations α_E .

Electric mobility

The probabilistic method for the electric vehicles is also used as a bottom-up approach for modelling the charging behaviour of various different electric charging stations expected in near future. Therefore, the analysed data (specific charging start time and recharged energy amount) of electric charging stations for different locations (public, company and shopping center) is used [9]. The electrical power of the charging stations p_{EV} for different locations and different installed powers (3,7/11/22/50 kW) is also included in the new methodology (see Figure 1).

Calculation of the residual power

The residual power p_{RES} is calculated for each time step t between the power of the decentralized generation unit p_{PV} , the power of the residential household p_{HH} and the electric charging stations p_{EV} .

$$p_{RES}(t) = p_{PV}(t) - p_{HH}(t) - p_{EV}(t) \quad (5)$$

Further investigations are planned in order to explore the effect of decentralized storage units on the influence of residual power reduction and peak power reduction. A positive residual power ($p_{RES} > 0$) can be stored in an electrical storage unit and a negative residual power can be supplied by the electrical storage unit. In the following the results of the residual power is expressed per single household.

SIMULATIONS

The following simulations based on analysed smart meter profiles are performed with the distribution functions for the winter period. The simulations are performed in MATLAB using the presented methodology (Figure 1) with the following parameters:

Residential households (HH):

- Number of households n_{HH} :
 - a) 10 HH b) 20 HH c) 100 HH d) 150 HH
- Power values: probabilistically generated ($\mu(t)$, $\sigma(t)$)

Photovoltaic power plant (PV):

- Peak power photovoltaic plant:
 - 1 – 15 kWp/HH
- Power values: recorded profile
- Mounting angle, orientation PV panels: 30°, south

The simulations are performed for a calculation period of 10 years with a time step resolution of 15 minutes. This is done in order to obtain enough power values. The load profile for the photovoltaic power plant is recorded for one year and used 10 times. In the following considerations the absolute value of the residual power $|p_{RES}(t)|$ is observed.

In Figure 4 the sorted duration curves of the residual power $|p_{RES}(t)|$ for 10 residential households with/without the photovoltaic power plant are shown.

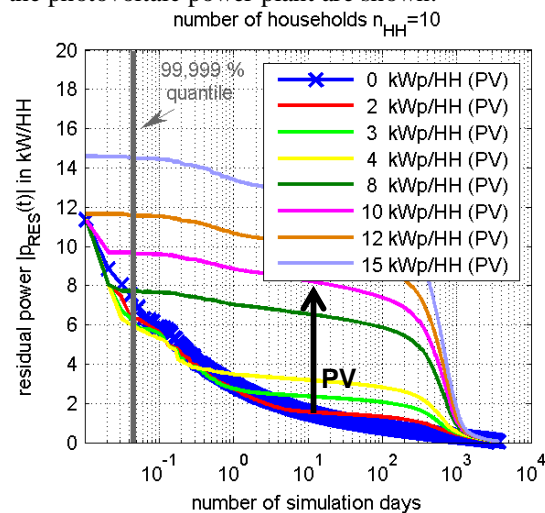


Figure 4 Sorted duration curves of the residual power for 10 residential households without PV (10 HH blue line) and with PV (10 HH with 1 kW/HH up to 15 kWp/HH (PV))

In Figure 4 the sorted duration curve of the residual power for example for 10 HH (blue line) without the photovoltaic power plant is used as the basis for the analysis. An increase of PV power (1 kWp/HH up to 15 kWp/HH) results in higher residual power values $|p_{RES}(t)|$ of the duration curve. In further investigations the absolute values of the residual power $|p_{RES}(t)|$ are used to calculate the peak power:

- 99.999 % quantile
- 99.990 % quantile
- 99.900 % quantile
- 99.000 % quantile

The previously mentioned quantiles are selected to estimate the occurring peak power of the 350.400 power values from the residual power with a time step of 15 minutes for 10 years. For an example by using the 99.999 % quantile, a possible overload of electrical equipment (e.g. transformer, power lines) for 53 minutes in 10 years can be assumed.

For a detailed analysis the calculated quantiles (e.g. 99.999 % - 99.000 %) of the residual power $|p_{RES}(t)|$ for 10 residential households with/without the photovoltaic power plant are shown in Figure 5.

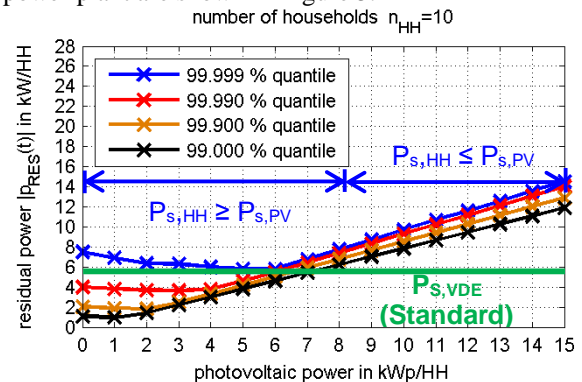


Figure 5 Peak power quantiles (99.999 % - 99.00 %) of the calculated residual power depending on the PV power per household (0 – 15 kWp/HH)

As shown in Figure 5, the residual power for 10 residential households, without taking the photovoltaic power into account (0 kWp/HH), is 7.5 kW/HH (blue line) for the 99.999 % quantile and 4.0 kW/HH (red line) for the 99.99 % quantile.

The calculation regarding the standard (VDE [1], TAEV [2]) with equation (2) results in 5.8 kW/HH (green line). This calculation shows that the peak power under consideration the conventional method is in-between the probabilistic quantiles (99.999 and 99.99 %). The peak power regarding the standard can be interpreted as a ~99,995 % quantile in winter.

The effect of the photovoltaic power (1 – 8 kWp/HH, $P_{S,PV}$) results in a reduction of the residual power $|p_{RES}(t)|$ by using the 99.999 % quantile. Higher photovoltaic power (> 8 – 15 kWp/HH, $P_{S,PV}$) results in a higher peak power for the combination of the residential households $P_{S,HH}$ and the photovoltaic power plant $P_{S,PV}$ by using the 99.999 % quantile.

The Table 1 summarizes the calculated quantiles of the performed simulations with and without the photovoltaic power plants. Additionally, the values according to standards (VDE [1], TAEV [2]) are listed as well as the peak power for the inverter of the photovoltaic power plant p_{PV} .

In Table 1, the performed simulations for a small amount of residential households (10 - 20 HH) show that the peak power values of the determined 99.999 % quantile are higher or equal to the standards used today (VDE, TAEV). The peak power values for the 99.99 % quantile (10 - 20 HH) are below the standard. As a result of this

investigation it is possible to integrate a photovoltaic power plant with the peak power for example 10 residential households of 7.5 kW/HH (99.999 %) or 4.0 kW/HH (99.99 %) depending on the used quantile.

Table 1 Peak power quantiles (simulation), peak power standard ([1], [2]) and photovoltaic power for 10 – 150 residential households (HH)

Number of household	Peak power				
	99.999 % quantile ¹⁾		99.99 % quantile ²⁾		standard [1],[2]
	ppv kWp/HH	pres kW/HH	ppv kWp/HH	pres kW/HH	Max kW/HH
10	-	7.5	-	4.0	5.8
10	7.5	7.2	4.0	3.8	-
20	-	4.8	-	2.5	4.9
20	4.8	4.5	2.7	2.4	-
100	-	2.1	-	1.2	3.6
100	2.2	1.9	1.4	1.1	-
150	-	1.3	-	1.0	3.5
150	1.5	1.2	1.2	0.9	-

When considering a higher number of residential households (100 - 150 HH) the simulations show a lower peak power (99.999 % and 99.99 % quantile) compared to the standard (VDE, TAEV).

CONCLUSION

The new methodology based on the statistic analysis of the measured smart meter profiles for residential households in an urban area using the log-normal distribution for each time step t and typical days and periods are used for generating probabilistically power values. The differences of the electrical power demand reflecting the individual personal-, labour-, and leisure behaviour of the residents are analysed and shown with the parameters of log-normal distribution ($\mu(t)$ and $\sigma(t)$). Depending on the number of households and the evaluated quantiles (99.999 %, 99.99 %) a peak power on the point of common coupling under consideration of own consumption can be calculated.

In general, the peak power due to the standard (VDE, TAEV) for a high amount of residential households (100 HH – 150 HH) is higher than the peak power quantiles. This leads to a significant over dimensioning of grid components (99.999 quantile). In contrast to a high number of residential households a small number of residential households (10 HH – 20 HH) the probabilistic approach shows a much higher peak power to be expected (99.999 % quantile). The peak power regarding the standard for a small amount of residential households can be interpreted as a ~99,995 % quantile in winter. This behaviour is also observed in practice. It must be noted that the peak power should not fall below the peak power of the photovoltaic power inverter.

The dimensioning for components of residential households in smart grids are either limited by the photovoltaic system or the loads on the consumer side beyond the photovoltaic power (water heating, air conditioning, electric mobility, electric storage units, heat pump). Therefore an optimization potential concerning the dimensioning of electrical equipment (power lines, transformers, grid structure, consumer equipment) can be evaluated.

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1) 99.999 % quantile results in a period of 53 minutes

2) 99.99 % quantile results in a period 526 minutes