

MONTE CARLO SIMULATION OF LOAD PROFILES FOR LOW-VOLTAGE ELECTRICITY DISTRIBUTION GRID ASSET PLANNING

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ABSTRACT

This paper presents a Monte Carlo simulation method for generating stochastic load profiles for models of low voltage (LV) electricity grids to support middle- and long-term strategic asset planning processes. Models that calculate aggregated loads in a deterministic way using a coincidence coefficient (simultaneity factor) do not give insight in the probability of an overload and eventual asset failure. Analysis of minute-to-minute load data obtained with Monte Carlo simulation, based on the characteristics and behaviour patterns of different household types, can provide more accurate probabilities of peak loads, especially for subordinate grids where individual consumption behaviours have relatively high impacts. Calculating this indicator for different future scenarios can help improve LV distribution grid capacity planning down to the component level.

INTRODUCTION: WHY MONTE-CARLO?

In electricity grid asset management, the minimum required grid capacity is typically determined on the basis of an estimated peak load. This peak load is usually calculated with the Rusck algorithm [1], i.e., by summing over all connected consumers the maximum consumption per individual consumer, multiplied by a so-called “simultaneity factor” [1, 2] or “maximum coincidence coefficient” [3]. This simultaneity factor depends on the number of connected consumers n , and may be computed by a function. Gwisdorf et al., for example, used $f(n) = \alpha + (1-\alpha) / n^\beta$ with parameter values $\alpha = 0.028$ and $\beta = 0.75$ for German distribution nets [3].

When aggregated peak loads are estimated using simultaneity factors (e.g., $f = 0.89$ for $n = 5$, $f = 0.80$ for $n = 20$, $f = 0.75$ for $n = 50$, and so on), the result is a single number. This provides no insight in the probability of the occurrence of a peak load that is higher than the capacity of the affected assets. If such a probability were known, this might help avoid investments in overcapacity [4].

The method and software presented in this paper aims approximate the probability distribution of peak loads, and especially the probability of a peak load at some point in the low-voltage grid that exceeds the affected assets' capacity (cf. Figure 1).

An important limiting factor for stochastic approaches that represent consumer loads as probability distributions

(see e.g., [5, 6]) is that the detailed load data at the household level that is needed to empirically determine this distribution is usually not available, and costly to obtain. To overcome this problem, load profiles of individual consumers are generated with a simulation model based on the characteristics and behaviour patterns of households (see also [6, 7]).

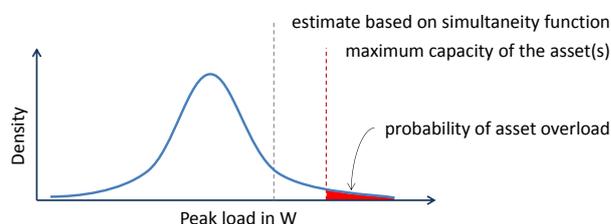


Figure 1. Probability distribution vs. deterministic estimate of aggregated peak loads

GENERATING LOAD DATA

In the present research, the individual consumers are households. Other types of consumer will be considered in the near future, and it is expected that the general approach as outlined in this section will also apply to, for example, schools, office buildings, and small and medium-sized enterprises.

Load data for a household are generated for each minute of a 24-hour period as depicted in Figure 2:

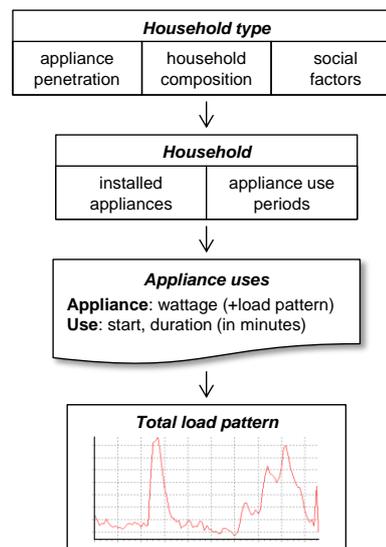


Figure 2. Generation of household load data

The actual power consumption of a household issues from the use of electrical appliances. Such appliance use will depend on the time of day (e.g., ovens and stoves before or at meal times, lights during early morning and evenings) and on the number of appliances installed in the household (e.g., television sets in different rooms). The periods of use and the frequency of use will depend on the time of year (seasonal variation) and day of the week (work/school or holiday) and on the type of household. The following sub-sections explain how these household parameters are specified.

Household Types

The use of electricity appliances in a household follows firstly from its composition: the number of people, the proportion of adults and children, and their age/social status (infant or school-going child, adult at home or working or studying fulltime/part-time). The size and type of the house will also affect electricity consumption, especially when electrical appliances for heating, cooling and lighting are used. Though gender may also influence appliance use, such differences of appliance usages are expected fall within the variance of the probability distributions for the frequency and duration of use for each appliance.

Presently, eight basic household types are defined as shown in Table I, with their composition based on the factors mentioned above. The percentages indicate the relative frequency of occurrence of these household types. These have been derived from Dutch census data.

Table I: Household Types and Their Percentages

| Household Type Code | Typical Member Composition | % |
|---------------------|--|-----|
| HH1 | adult staying at single studio | 32% |
| HH2 | single parents with children | 6% |
| HH3 | working couple without children | 4% |
| HH4 | working couple with children | 9% |
| HH5 | couple without children, one is house-stay | 19% |
| HH6 | couple with children, one is house-stay | 20% |
| HH7 | retired couple | 4% |
| HH8 | student house | 6% |

Appliances

The type and number of electrical appliances in a household will vary widely. A general penetration degree for each type of appliance has been derived from several data sources on the Dutch society.

Number of Appliances in a Household

The actual number of appliances of a particular type installed in a household is based on this general penetration degree and on household type characteristics, and also on the appliance category: house-type, shared-type or individual-type. *House-type* are those appliances

that are typically installed regardless of the household composition (e.g., heating devices). *Shared-type* are those appliances that are used in a shared manner by several household members (e.g., a TV set or a refrigerator). Additional shared-type appliances will be installed when the household size exceeds certain thresholds. *Individual-type* are those appliances that belong to members individually, so that their usages are completely independent from each other (e.g., charging devices for portable electronics). Table II shows how a general appliance penetration degree P_0 is modified for appliances in the three categories.

Table II: More Specific Appliance Penetration Degrees

| Appliance category | Description | Derivation of P * |
|--------------------|--|--|
| House-type | penetration degree is independent of household composition | $P = P_0$ |
| Shared-type | penetration degree is related to # of members | $P = P_0 + \text{hh size} / 5$ |
| Individual-type | penetration degree is directly linked to # of members | $P = P_0 \times (\#adults + \#children / 2)$ |

* Notes:

1. For shared-type: assume that when over 3 children are in the household, then an additional appliance is installed.
2. For individual-type: assume that 50% of the children are old enough to have their own appliances.

Use Frequency per Appliance

The use of appliances may be related to the time of day. Lights are the obvious example, but many other appliances are used in time-related activities (e.g., hair dryer after bathing, dishwasher after meals). These activities themselves are not specified, but they are taken into consideration when for each appliance in a household type, one or more periods in a day (24 h) are identified, and for each of these periods, the number of appliance uses is specified as a probability distribution. The parameters of these distributions are set in accordance with the parameters of the household type, notably the number of persons.

Use Duration per Appliance

The typical duration of use is presently specified as a single probability distribution for each appliance. Although correlations with household parameters are conceivable, these are assumed to “dissolve” in the variance of the duration.

Power Use Profiles of Appliances

The power consumption of programmed appliances such as washing machines and microwave ovens is not constant, but tends to alternate between different levels according to a pattern (e.g., fill-heat-wash-drain-spin-rinse-spin). For the most common appliances, such patterns are presently being investigated using a Watts meter/recorder; they have not been included in the simulations to date.

GENERATION OF A LOAD PROFILE

A load profile for a household is represented as an array L of 1440 real numbers, where each number corresponds to the load in Watts during one minute of a 24-hour period (starting at midnight). The values for $L(i)$ are computed according to the following algorithm:

```

set  $L(i) = 0$  for ( $i = 0 \dots 1440$ ) ; // initialize load to 0 for the 24 h period
for each connected household  $h$  {
  select household type of  $h$  by drawing from an empirical
  distribution like the one in Table I ;
  for each appliance type  $a$  {
    if penetration  $p$  of  $a$  is specified for  $h$  {
      draw number  $n$  of installed appliances of type  $a$ 
      from distribution  $p$  ;
      for each installed appliance  $a(i)$  ( $i = 1 \dots n$ ) {
        draw wattage  $w$  from distribution specified for  $a$  ;
        for each appliance use period  $aup$  specified for  $a$  in  $h$  {
          draw start time and duration of  $aup$  ; *
          draw # uses  $u$  from distribution specified for  $a$  in  $h$  ;
          sum = 0 ;
          for ( $i = 1 \dots u$ ) {
            draw duration of use  $du(i)$  ; // in minutes
            sum = sum +  $du(i)$  ;
          }
          rest = duration of  $aup$  - sum ;
          for ( $i = 1 \dots u$ ) {
            determine start of use  $su(i)$  ; **
            for each minute  $m$  from  $su(i)$  to  $su(i) + du(i) - 1$  {
               $L(m) = L(m) + w$  ;
            }
          }
        }
      }
    }
  }
}
    
```

Notes:

* The start time and duration of use periods are also specified as probability distributions to avoid, for example, that all households cook dinner at the same time.

** The start times $su(i)$ (in minutes since midnight) are determined by distributing the remaining time $rest$ in-between the uses. The regularity of this “interspacing” can be specified for each appliance (0 = random, 1 = strictly regular intervals). In this way, the behaviour of thermostat-controlled devices can be approximated (see for example the fairly regular peaks on the left hand side of Figure 4, which are produced by the air conditioner).

SIMULATION OF AN LV GRID

The QWatts software developed by the second author allows rapid entry of a radial power distribution grid as exemplified in Figure 3. Each arrow denotes a single household. A grid can be assessed under different scenarios, where each scenario defines the relative frequency of occurrence of selected household types. Seasonal variations and future scenarios, and also exceptional situations, can be specified by defining additional household types, e.g., “2 adults and 3 children all at home in mid-winter”, or “small gathering with friends for BBQ and then watch a World Cup football match”.

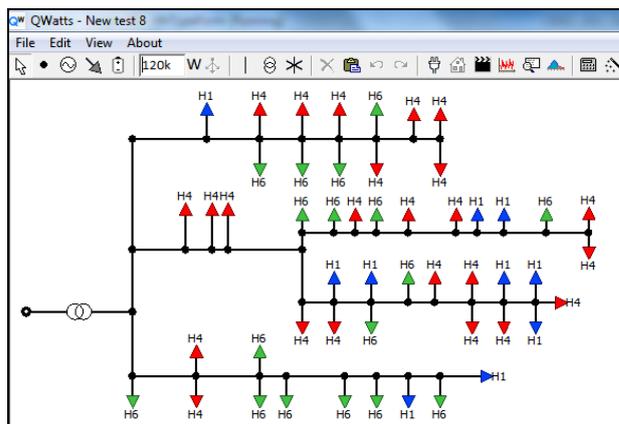


Figure 3. Sample network layout in QWatts

Given a scenario and a grid layout, household types are randomly assigned. The example in Figure 3 shows the result for a 3:5:3 ratio for three household types. Load profiles are then generated according to the algorithm specified in the left-hand column of this page. Loads are aggregated at each junction of the grid simply by summation (for each minute) of the loads on the branches departing from that junction. Electrical properties such as voltage drop are ignored. Figure 4 shows an example of a load profile of a single household, Figure 5 of the aggregation of 50 load profiles.

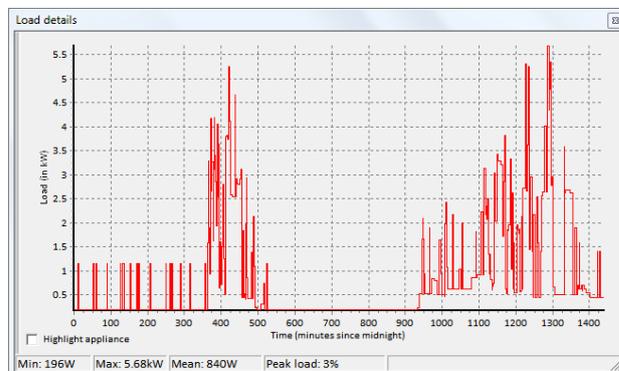


Figure 4. Load profile generated for a single household

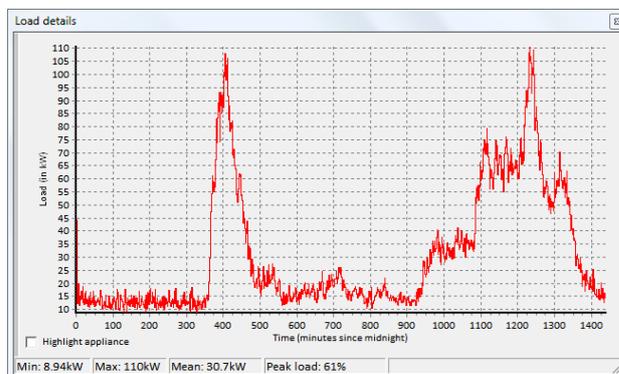


Figure 5. Aggregation of 50 load profiles

To obtain insight in the probability distribution of peak loads, a histogram like the one in Figure 6 is produced by executing the presented algorithm a large number of times while collecting data on peak loads for every node in the grid. A Monte Carlo simulation comprising 1000 runs for the grid in Figure 3 takes about 40 seconds. The QWatts software can produce graphs as shown in this paper, as well as detailed overviews of appliance uses, for any node selected in the grid.

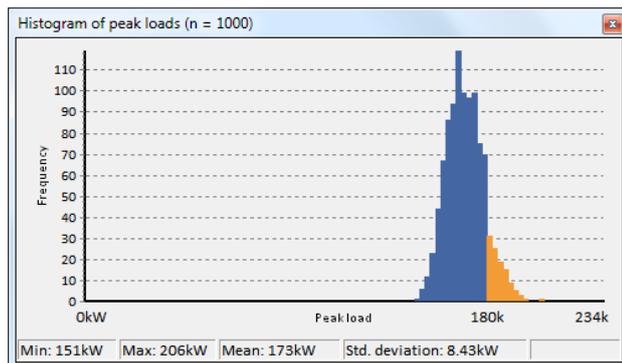


Figure 6. Histogram of peak loads

VALIDATION

The results presented here are truly a “first try”; no effort has been made yet to validate the profiles. The figures show that the peaks and daily consumption are rather high. This may in part be explained by the air conditioners that were assumed to be switched on while people were in the house (a “hot summer day” scenario).

Rigorous validation is needed before the outcomes produced by the QWatts software can be used to support the asset capacity planning process of distribution network operators. Several validation activities are foreseen. Firstly, the properties of the household types defined so far, and the appliance uses they generate, will be scrutinized to see whether they are plausible. Global indicators such as the peak load per household (which should not exceed the limits set on household connections) and the extrapolation of the electricity consumption in 24 hours to annual consumption (which should be within normal range) will be used to assess the plausibility of appliance use.

Secondly, aggregations over large numbers of households will be compared with empirical transformer load data (corrected for non-domestic power use such as street lights) to check whether the overall 24h patterns are plausible.

Thirdly, a data set that has been collected from individual households with smart meters installed will be used to verify through statistical analyses whether the generated load patterns differ significantly on characteristics such as the (minimum, maximum, mean, etc.) height, duration, frequency, and interspacing of peaks, as well as their distribution in time.

CONCLUSION

Although the household type profiles still need to be checked and eventually validated using empirical data, the first, preliminary results are encouraging, as they confirm the idea [6, 7] that bottom-up Monte Carlo simulation can provide relevant information. A quick analysis of the simultaneity of peak loads suggests that the simultaneity factor for $n=50$ ranges between 0.48 and 0.52, whereas its calculated value (using $f(n) = \alpha + (1-\alpha)/n^\beta$ with parameter values $\alpha = 0.028$ and $\beta = 0.75$ as reported in [4]) equals 0.75. The difference is a sign that there may be more slack capacity in LV distribution networks than is generally assumed. Evidently, more rigorous analysis and validation is needed to substantiate this.

A limitation of the presented method is that the analysis only considers loads; voltage drops are ignored, whereas in rural or suburban LV networks with rather long strings, the critical voltage limits are generally reached before the critical loading [4]. This limitation can be overcome by performing follow-up analyses on a representative sample of grids using more sophisticated grid analysis software.

Acknowledgement

This work was supported in part by Enexis B.V., the Netherlands.

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