LOAD MODELS FOR ELECTRICITY DISTRIBUTION PRICE REGULATION

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ABSTRACT

The Finnish Energy Authority, which regulates electricity distribution network operation, was given a new task in 2017 when the law on electricity markets changed. The new law states the distribution fees in any consumer segment can increase a maximum of 15 % during a period of 12 months. To enforce this law, the regulator must be able to calculate average distribution charges for different customer segments. In this paper, we aim to create type consumer load models that can be used to calculate average distribution charges with a wide variety of distribution tariffs. The tariff structures are not regulated and they can contain differently defined time-of-use periods, peak periods, and maximum demand calculation principles. In addition, possibility to evaluate novel distribution tariffs with power and tier limits is considered.

INTRODUCTION

Electricity distribution business is a natural monopoly and is regulated to prevent distribution system operators (DSOs) from misusing their monopoly position. In Finland, the regulator is using revenue caps to limit DSOs' profits to a reasonable level. In addition, the recently updated electricity market law states that the distribution fee of an average consumer can increase a maximum of 15 percent during a period of 12 months [1]. The legality of the distribution charge increase is evaluated separately for each customer segment.

Supervision of the above mentioned price increase cap requires information on the electricity consumption in each customer segment. The existing type consumer load profiles can be used to evaluate only the pricing of volumetric tariffs: single rate and time-of-use (ToU) tariffs. Assessment of tariffs that have also demand components requires knowledge on the peak loads.

Maximum demand, which the distribution system is designed to meet, is a major determinant for the DSO's costs. Since the widespread introduction of smart meters is enabling peak demand measurements, distribution tariffs with demand components are trending and they are offered to smaller and smaller electricity consumers. From the regulator and price increase evaluation point-of-view, the demand-based distribution tariffs are problematic. At present, there is significant variation in how the DSOs define the maximum demand and providing tools for assessing every possible option can be challenging.

In this paper, we present a new load model structure that enables distribution price evaluation with most foreseeable and reasonably designed tariff structures. Our solution combines traditional customer class load profiles and peak power tables that contain the necessary information to analyse demand-based distribution tariffs. In addition, a methodology for selecting the type consumers is presented. The proposed load modelling methodology is demonstrated by creating new type consumer load models for Finland. The usage of the new load models with distribution tariffs of different kind is also discussed.

We want our load models to be future proof and therefore consider recently discussed future tariff structures [2], for example, power-limit tariffs and tiered tariffs. Evaluating distribution charges inflicted by this type of tariffs requires knowledge not only from the average peak powers or interval energies but also from the distribution of these powers and energies. Since the DSOs can choose the power limits freely, we want to model the loads with continuous distribution functions. Unfortunately, no single distribution function is able to model all the load distributions accurately. In some cases, the use of mixture models, such as the Gaussian mixture model [3], is necessary.

To make things clear, it should be noted that the new type consumer load models, are separate from the load profiles used in distribution network calculation [4] or in balance settlement. The load models presented in this paper are used in price increase cap regulation, which in turn is separate from the revenue cap regulation. In addition, these will be used in the compilation of price statistics and public information announcements.

SELECTION OF TYPE CONSUMERS

Before the type consumers can be modelled, we must define what we mean by "type consumer" and find out what the most typical consumers are. In this paper, the type consumer is characterized by the type of activity, fuse size and annual energy consumption. The type consumer load model describes the average behaviour of consumers with these selected attributes. The modelled consumer segments are selected by analysing interval measurements and customer information data.

The study material contains smart meter measurements from ten DSOs located in different parts of Finland. The number of consumers with valid hourly measurements is 710 463 and all the measurements cover a period of at least two years between the years 2013–2018. Some data from the DSO's customer information systems (CISs) are also available: fuse size, number of phases, postal code, and type of activity. Temperature measurements for each studied area are downloaded from the Finnish Meteorological Institute's open data repository [5].

Clustering

The consumer types that most accurately represent the consumer spectrum are selected with the help of clustering analysis. First, the consumers are clustered using weighted k-means algorithm and two-stage clustering procedure described in [6]. In short, the temperature normalized interval measurements and condensed into pattern vectors describing the hourly profile of a typical week in each month, pattern vectors are normalized to mean of one, and then these normalized patterns vectors are clustered using the consumed annual energies as weights.

Two different approaches are taken to find the most important consumer segments. In top-down analysis, the consumers are first clustered into 50 clusters, and descriptive names are given to each cluster based on their load profile and customer content. The latter phase is done manually and requires some experience on load research. Then the clusters with similar descriptions are combined into larger main consumer segments. In bottom-up approach, the starting point is five clusters, the number of clusters is gradually increased, and changes in clusters are observed.

New type consumers

When selecting the new type consumers, we used the insight gained from cluster analysis and noted that as many consumers as possible should be able to identify with the type consumers. Compatibility with the old type consumers, existing distribution tariff structures, Eurostat consumer classes, and data structures used in the upcoming Finnish datahub were considered. In addition, feedback from the regulator, DSOs, and interest groups in the energy sector were received in common workshops.

Finally, the 14 type consumers presented in table I were defined. Fuse size for each type consumer was selected based on the mode of the fuse sizes in the corresponding consumer segment and the annual energy consumption was selected based on the average energy consumption.

Type consumer sets

Once the type consumer characteristics were defined, the consumers that fit best to each type consumer class where selected. The results from the clustering with 50 clusters were examined and only consumers that fulfilled the following five conditions were selected to each type consumer set:

1) Consumer belongs to a cluster with similar description as the type consumer
2) Distance from the cluster centroid belongs to the shortest 80% within that cluster.
3) Activity information in CIS conforms with the type consumer definition
4) Fuse size matches with the type consumer definition.
5) Annual energy consumption matches (roughly ±20%) with the type consumer definition.

Conditions 1 and 3 filter out mistakes done in both clustering and in activity type classification. Condition 2 acts as outlier filtering. After checking all these conditions, we are left with uniform type consumer sets of different size. The largest type consumer set was 3-phase apartments with 17 524 consumer and the smallest was 3-shift industry with 24 consumers.

LOAD PROFILES

Type consumer load profiles, in the year 2018 calendar, were calculated from the type consumer sets' interval measurements. Active power profiles were calculated for all type consumers and reactive power profiles for those with fuse size larger than 63 A. For every hour of the year 2018, similar hours in a similar day type and time of the year (±15 days) were searched from the measurement period, and average hourly energy on these hours was calculated. Before averaging, the interval measurements were normalized to correspond the load in long-term (30 years) average temperature and to match the type consumer’s annual energy.

In addition to saving the averages, the distributions of the hourly energies were modelled and saved. Four different distribution models were fitted to the data: normal distribution, log-normal distribution, Gaussian mixture model (GMM), and a mixture of log-normal and normal distributions (denoted here as Logn+GMM). Each distribution model has pros and cons. The normal

Table I. *New type consumers.*

	Activity description	Fuse size (A)	Energy consumption (MWh/a)
1	Summer cabin	3×25	1.0
2	Apartment, 1-phase connection	1×25	1.5
3	Apartment, 3-phase connection	3×25	2.5
4	Detached house, no electric heating	3×25	5
5	Detached house, energy efficient, electric heating	3×25	10
6	Detached house, direct electric heating and timed domestic water heater	3×25	16
7	Detached house, electric storage heater	3×25	19
8	Outdoor lighting, pecu switch	3×35	34
9	Farm, cattle farming	3×35	42
10	Business, short opening hours	3×63	50
11	Industry, small-scale, 1-shift	3×160	180
12	Business, long opening hours	3×400	600
13	Industry, connected to medium voltage network, 1-shift	-	1000
14	Industry, connected to medium voltage network, 3-shift	-	6000

distribution is mathematically the most convenient but usually the least accurate. The log-normal distribution describes electric load distribution better but summing up the distributions is more difficult. The mixture models are more complex but are usually even more accurate and can also describe multimodal distributions.

In this study, mixture models with two components were used. Both mixture models were trained using the expectation maximization (EM) algorithm [4]. In case of Logn+GMM, both possible orders for log-normal and normal distribution were tested and the order with the best accuracy was selected.

With the above described distribution models, the distribution of hourly energies can be stored by saving only a few parameters. In addition, the distribution histograms were saved. Histograms can also be used to compress the distribution data and are simpler to utilize.

PEAK POWER TABLES

When calculating peak powers, we must take into account that DSOs have many different ways to define the maximum demand used in billing. The maximum demand can be defined as annual or monthly peak power, as the highest peak power or as an average over the N highest peak powers, and the time interval from which the peak power is calculated can be limited to varyingly defined peak seasons and hours. Therefore, annual and monthly peak power tables containing information from many of the highest peak powers are required.

Our solution has type consumer specific peak power tables for annual and monthly active power. Each peak power table contains the 100 absolutely highest hourly powers. If these 100 powers do not contain at least the 20 highest powers from each presently used peak power determination interval, these missing power values are added to the end of the table. In addition, the distribution of each peak power is modelled using the same methods that were applied to the load profiles. For large (>3×63 A) type consumers, peak power tables for reactive power are also calculated.

Peak power magnitude

The peak powers are calculated from the non-temperature normalized interval measurements of the type consumer set. In case of annual peak powers, the calculation process is:

1) Select consumer's measurements from one full (rolling) year, and sort them in descending order.
2) Repeat step 1 for all fully measured years and other consumers in the set.
3) Combine results into one matrix.
4) Calculate how each highest power depends on the consumer's annual energy (linear regression) and normalize all powers to type consumer's annual energy.
5) Calculate means, correlations, distribution parameters and histograms.

The same procedure is applied when calculating the monthly peak powers.

If the type consumer set is not completely uniform, the distribution of the peak power can be multimodal. Figure 1 depicts the annual peak power distribution in type consumer set 3. Mixture models are clearly needed to model this distribution. In this case, the multimodality is probably caused by electric sauna stoves, which exist only in some apartments.

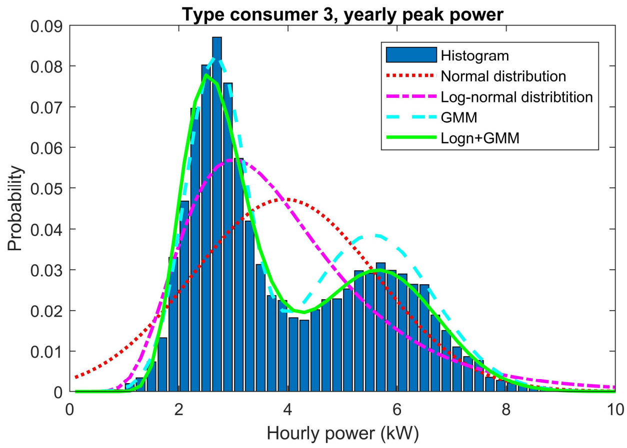

Figure 1. *Annual peak power histogram and distribution models for type consumer 3 set (apartments).*

Peak power timing

In addition to magnitude, we are also interested in the timing of the peak. However, defining the peak hour is challenging, since the peak power timing varies greatly. As demonstrated in Figure 2, the peak powers within type consumer set are often distributed so widely that even the most likely peak hour contains only a fraction of the set's peak powers. Additionally, we observed that in, some cases, the most likely peak hour could be the same for up to the 20 highest hourly powers. The timing is further obscured by the fact that in many consumer classes the peak power is highly dependent on the outdoor temperature. Since unambiguous definition of the peak timing is difficult, we compromised and determined the peak power timings from the previously calculated temperature normalized load profiles.

APPLICATION WITH PRESENT TARIFFS

The calculation of type consumer distribution charges is relatively straightforward with most presently used distribution tariffs. When the volume and demand charges depend linearly on the energy consumption and peak power, only the mean values stored in the load profiles and peak power tables are needed.

Using the load profiles and the year 2018 calendar information, energy consumptions for different ToU periods can be calculated. In cases where the tariff has a demand component, the peak power (within the defined peak power period) is simply looked up from the applicable peak power table and multiplied with the demand charge. Even when the maximum demand is defined as a mean of several peak powers, it can be calculated simply by averaging the peak powers picked up from the peak power table.

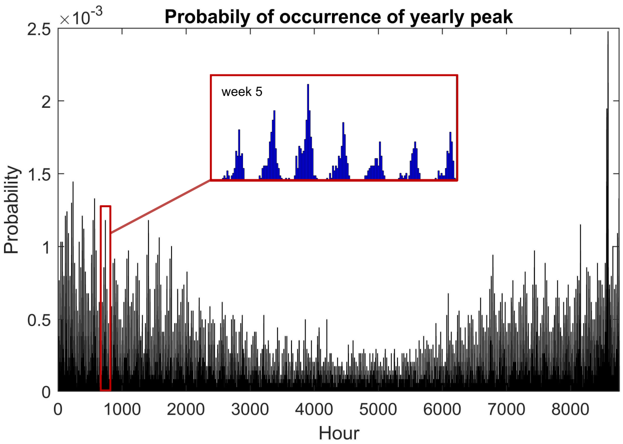

Figure 2. *Probabilities in which the yearly peak power of type consumer 3 occurs at each hour of the year.*

APPLICATION WITH NOVEL TARIFFS

Many novel tariff structures proposed in literature contain energy or power limits [2], [7], which make the distribution charges nonlinear. Such tariffs include, for example, power limit tariff, threshold power tariff, and tiered (by interval energy) tariff. When the distribution charge depends nonlinearly on the maximum demand or interval energy, the calculation of average distribution fees requires knowledge from the distribution of peak powers or interval energies. This is where the previously described distribution models and histograms become relevant. With continuous distributions, it is possible to calculate the average distribution fees regardless of how the energy or power limits are chosen. The following subsections give some examples. With histograms, the calculation is simpler, but accurate only if the limits coincide with the histogram bin edges. If limits do not match with the edges, frequencies on each side of the limit could be interpolated from the histogram data. If the bin count is large enough, errors caused by the interpolation are probably negligible.

Power limit tariff

In a power limit tariff, the demand charge is based on discrete peak power limits (a.k.a. bands). Each power band has its own fixed price. Figure 3 shows yearly peak power histogram for one type consumer set and some power limits. The average demand charge for a type consumer set is calculated with equation

$$C_{demand} = \sum_{i}^{n} p_i \times H_i \,, \qquad (1)$$

where n is the number of power bands

p_i is probability that peak power is in band i

H_i is demand charge for band i.

The probabilities p_i can be calculated from the histogram, or from the distribution models. In case of single distribution models, the probability p_{12} that peak power is between powers P_1 and P_2 is calculated with equation:

$$p_{12} = \Phi(P_2; \mu, \sigma) - \Phi(P_1; \mu, \sigma), \qquad (2)$$

where Φ is cumulative distribution funktion for the used distribution

μ and σ are distribution parameters for the used distibution.

In case of mixture models, the probabilities are weighted sums of values given by (2).

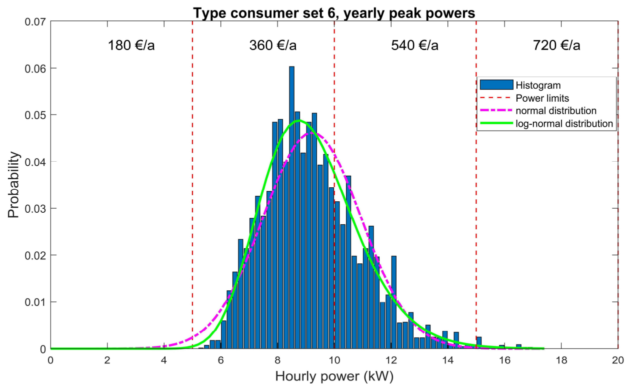

Figure 3. *Annual peak power models for type consumer 6 and some power limit and demand charge examples.*

Threshold power tariff

In a threshold tariff, demand charge is applied if a predefined threshold power is exceeded. Only the power exceeding the threshold in billed. In this case, to calculate the type consumer's average demand charge, we need to know both the probability of exceeding the threshold and the mean of those powers that exceed the threshold. The probability can be calculated applying (2) and the expectation value for the exceeding power can be calculated from truncated distributions. For truncated normal distribution, the necessary equations can be found in [8]. For log-normal distribution, the equation needed is

$$E(P|P_1 < P < P_2) = e^{\mu+\frac{1}{2}\sigma^2} \times \frac{\Phi(\sigma-\alpha; 0{,}1) - \Phi(\sigma-\beta; 0{,}1)}{\Phi(\beta; 0{,}1) - \Phi(\alpha; 0{,}1)}, \qquad (3)$$

where $\alpha = \frac{\ln P_1 - \mu}{\sigma}$

$\beta = \frac{\ln P_2 - \mu}{\sigma}$

Φ is cumulative density function for *normal distribution*

μ and σ are distribution parameters for log-normal distribution.

In case of threshold power tariff, P_1 is the power threshold and P_2 is infinite.

Note: beware of catastrophic cancellation when both P_1 and P_2 are far at the distribution tail.

Tiered tariff

Here we study a tiered tariff, where the consumption charge is dependent on the interval energy in a stepwise manner [2]. In this case, the yearly volumetric charge is calculated as

$$C_{volume} = \sum_{1}^{M} \sum_{i=1}^{n} p_i \times E(e_i) \times H_i \, , \qquad (4)$$

where M is the number of intervals in a year
n is the number of tiers
p_i is probability that the interval energy is within tier *i*
$E(e_i)$ is expectation value for interval energy within tier *i*
H_i is consumption charge for tier *i*.

The probabilities and expectation values can be calculated using, for example, equations (2) and (3). In addition, the use of histograms is possible.

Challenges

If the maximum demand is defined as an average over the N highest peak powers, we must first calculate the distribution for this mean power. Assuming we did not know which peak powers are averaged, when the peak power tables were calculated, we need to do this based on the individual peak power distribution models. Furthermore, we have to take into account that the peak powers are highly correlated. With these preconditions, out of the tested distributions, normal distribution is the only one that can be used to calculate the distribution of the mean analytically. The sum, and thus the mean, of log-normally distributed correlated variables could be approximated with another log-normally distributed variable [9] but calculating the parameters of this distribution is complicated. The need to know the peak power correlations increases the load model size significantly. The correlation matrices become huge and numerous if all the possible correlations are considered.

Solutions

The load models become immensely complex, if they have to cover all imaginable tariff options. The need for correlation matrices and mean distribution calculation could be eliminated, if the maximum demand calculation principles were harmonized, or at least limited to a finite number of possibilities in tariffs with peak power limits. Then the distributions of the N highest peak powers could be calculated, in advance, directly from the type consumer sets' interval measurements.

CONCLUSIONS AND FUTURE WORK

The regulator needs new load models to enforce the law on the price increase cap. In this paper, we updated the type consumer definitions and created load models that can be used to evaluate the average distribution charges in each type consumer segment. Our goal was to enable price calculation with a wide variety of distribution tariffs. With present tariff structures, the new load models can easily cover all sensible tariff variations. However, with novel tariff structures that contain energy or power limits, the calculation of average distribution charges becomes complicated and even impossible in some cases. If these tariff structures are taken into use, we must discuss within the electricity industry, whether the issues are solved with regulation or by developing the load models further.

In the future, new consumer segments are expected to emerge, for example, prosumers and electric vehicle charging points. The behaviour of consumers is also believed to change, when dynamic retail tariffs and power based distribution tariffs become more common. These changes, together with possible transition to shorter measurement intervals, require that the load models are kept up-to-date.

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