STOCHASTIC GENERATION OF HOUSEHOLD ELECTRICITY LOAD PROFILES IN 15-MINUTE RESOLUTION ON BUILDING LEVEL FOR WHOLE CITY QUARTERS

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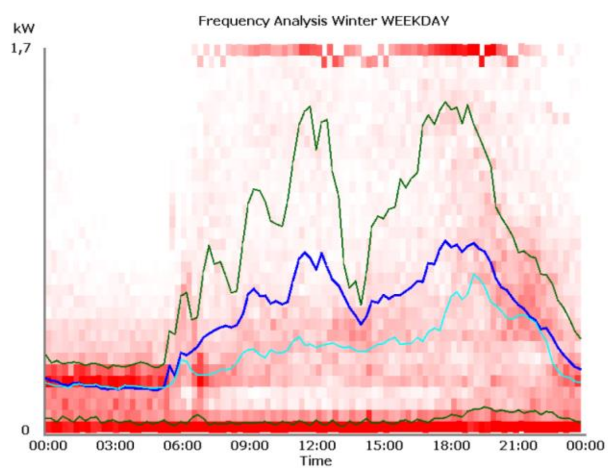
Overview

This paper presents a new method for generating synthetic household electricity load profiles by using a small data set of measured time series data as an input. In general, electricity demand can be determined by either bottom-up or top-down methods. The bottom-up method is very detailed, taking single devices and user occupancy into account [1]. Top-down modelling uses regionally aggregated data [2] to draw conclusions about consumption based on building characteristics and attributes. The method presented is neither one of the mentioned above but a black-box modelling approach. Goal of this study is to simulate building electricity demand with as little input data as possible, while taking stochastics and randomness of occurrences into account. Additionally, this method should be able to produce synthetic time series with a customizable resolution on single building level for whole city quarters (up to several 100 buildings). Simultaneously the time complexity of the algorithm should be reasonable. Most of the freely available existing synthetic load profile generators work with a bottom-up approach, like [3] or [4] and are applicable only for a certain amount of households/buildings before the computational effort gets impractical. This study uses 3D CityGML files as a source of information for building properties and then applies the new method to the building stock using SimStadt as simulation platform.

Methods

Measured data from smart meters were used as data source. Six single-family houses, situated in a small village in the district of Heilbronn, were monitored over eleven months in five-second resolution. For this study, the measured values were averaged to 15-minute time steps. In addition to this conversion a data cleaning process was performed. Invalid time series data was removed from the sample set, such as e.g. negative measurements or data gaps. All valid time series curves were classified into workdays, Saturdays as well as Sundays. Furthermore, the data sets were divided into seasonal time periods: summer, winter and transitional period (spring/fall). Through this procedure nine subsets for each option were created. All valid data for these subsets was now layered on top of each other in one graph. From the superimposed curves, histograms can be extracted as seen in **Fig. 1.** The x-axis denotes the time in 15-minute resolution, resulting in 96 time slices for one day. The y-axis defines the electricity consumption in kW. For every single time slice one histogram is created by dividing the interval between the maximum and minimum measured value into 50W-segments. Every 50W-segment represents a class interval of the histogram. Afterwards every measured data point is sorted into the class intervals. The red color saturation depends on the number of data points in a class. The stronger the coloration, the more data points lie in the class interval. The blue line shows the average consumption over the whole subset "winter weekday", the turquoise curve shows the median. The dark green graphs indicate the 20th and 80th percentile.



Legend:
Average median 20^{th} and 80^{th} percentile

Fig. 1: example of the analysis of winter weekdays with fixed class size and cut-off spikes

Based on the histograms for every time slice synthetic electricity load profiles are generated by applying a pseudo-random number generator. For selecting a class the random number generator is weighted according to the number of data points in each class interval, meaning a probability is assigned. Within the selected class interval, the final value of the synthetic load profile is picked by an unweighted pseudo-number generator. These steps are repeated for each time slices resulting in a daily electricity load profile.

Results

The above-mentioned method is applicable for a large amount of residential buildings with customizable resolution (yearly, monthly, weekly, hourly and 15-minutes). The synthetic load profiles show a desired variability of the peak loads, thus avoiding peaks in demand at the same point of time for every single load profile. In a first validating step, 1000 of synthetic load profiles were generated, summed up, averaged and compared to the measured averaged load profile. In **Fig. 2,** the averaged load curves for 1000 generated load profiles are marked in blue on the left side and for 100 on the right side. The comparison to the measured average load profile is indicated in red. It is evident that the averaged load curve with about 100 generated synthetic load profiles already converges well to the originally measured average consumption. For further validation a different data set of measured household electricity consumption will be compared to the generated load profiles.

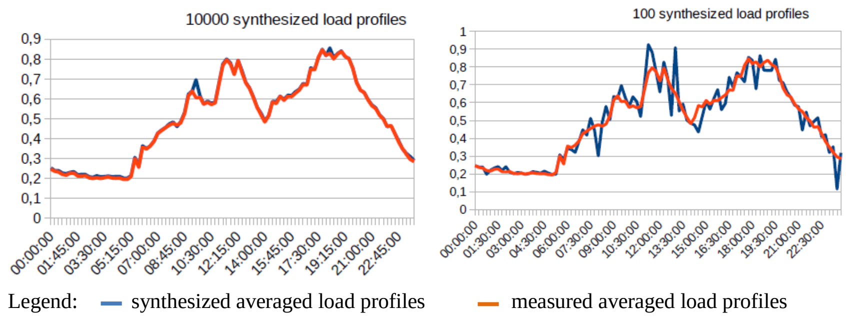


Fig. 2: Comparison between measured and synthetic averaged load profile, on the left with 1000, on the right with 100 synthetic generated load profiles

Conclusions

The described method shows good results for the generation of distinguishable synthetic load profiles with reasonable computational effort for residential buildings. Since the synthetic profiles converge towards the average measured consumption, the generated curves can reflect realistic measurement data. However, the process does not take the autocorrelation between data points into account, therefore the synthetic load curves display more spikes than their measurement counterparts [5]. Autocorrelation can be considered in further studies by adding further weightings to the class intervals. Moreover, this method is not only applicable to household electricity consumption for residential buildings. With smart meter data from different building types the method can be repeated, resulting in building type adapted synthetic load profiles.

References

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