DEVELOPMNET OF PROBABILISTIC DAILY DEMAND CURVES FOR DIFFERENT CATEGORIES OF CUSTOMERS

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ABSTRACT

The paper presents methodology for developing probabilistic daily demand curves for different categories of customers. Demand data for different end-users in different load sectors are collected and converted to demand data for different load categories in order to develop deterministic Decomposed Daily Loading Curves (DDLC) for different load sectors. After developing DDLC for different load sectors, relevant uncertainties are incorporated and probabilistic DDLC are developed. With DDLC for different load sectors, different groups of deterministic and probabilistic DDLC for overall demand can be developed.

INTRODUCTION

Due to inevitable demand variation during the day and season associated with end use customers' operation cycles and habits, the compositions of loads forming total demand at network bulk supply point change. This results in significant uncertainty in contribution of different load categories to total demand in different load sectors as well as to uncertainty of composition of the overall demand at the bus. Consequently, there is uncertainty in demand response to network disturbances, and more importantly, in the overall network dynamic behaviour. The proliferation of new types of loads (power electronics interfaced load, efficient lighting, electric vehicles, etc.), small distributed generators, and to a certain extent already modified customer behaviour introduces further uncertainty in demand composition. In Demand Side Management (DSM), shifting certain amount of demand at different time of day would help balance generation and demand in the network but will also change the composition of demand at those times. The change in composition of demand would further affect its dynamic response to network disturbances at those hours, which could significantly influence the overall network voltage and angular stability. Being able to predict demand response following network disturbances at any given time of the day would facilitate efficient active demand management and ensure stable and secure operation of the power system as a whole. In order to demonstrate such stochastic characteristics of close to real time load contributions for both different classes of customers and the overall demand, probabilistic Decomposed Daily Loading Curve (DDLC) is developed in this paper.

Probabilistic DDLC is daily loading curve with probabilistic segmentations which not only segregates the overall demand into different load categories, but also indicates the possible ranges of such segmentation. Development of probabilistic DDLC should start from the development of deterministic DDLC. Deterministic DDLC is daily loading curve with deterministic segmentation that illustrates the power consumed by typical end-users' devices or by different categories of customers. Deterministic DDLC for different load sectors at different parts of the world have been developed in the past. In [1], DDLC for residential, commercial, and industrial load sector as well as overall demand in California, US are derived. Daily demand data for different load types on different days during different seasons in Californian commercial sector are measured and recorded by WECC in [2]. DDLC for general UK residential load sector during the winter are provided in [3]. In [4-6], DDLC for residential load sector for different European countries (France, Italy, Germany, Sweden etc.) are provided, Additionally, [4] provides variation in mix of load sectors contributing to the overall demand at different times of day. The DDLC developed in the past illustrate general demand composition at different parts of the world. The uncertainty in demand, however, is almost completely ignored in the past work, and the concept of probabilistic load contribution to overall demand at bulk supply point is very seldom, if at all, mentioned.

In this paper, stochastic characteristics of different load categories and their contribution to overall demand are taken into account. The approach taken is illustrated in Fig. 1. Available demand data for different load types are used to develop probabilistic DDLC for different load categories by taking into account the uncertainty in both, the demand and the composition of demand.

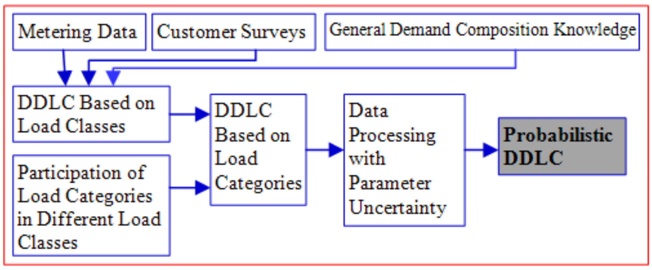

Fig. 1. Methodology for development of probabilistic DDLC

DETERMINISTIC DDLC

Demand data for different load types or end-users are collected for different load sectors, and converted to demand data of different typical load categories to create deterministic decomposed daily loading curves (DDLC).

DDLC based on load types

Fig. 2 displays a DDLC of typical commercial load sector based on load types, derived from original demand data for different end-users provided in [2]. The peak demand is normalised to 100 for ease of comparison. Different types of loads participating in commercial load sector are highlighted by different colours and patterns and listed beside the figure in sequence. Some appliances such as air conditioning, process and water heating devices are participating very little in total demand and are almost invisible in the figure.

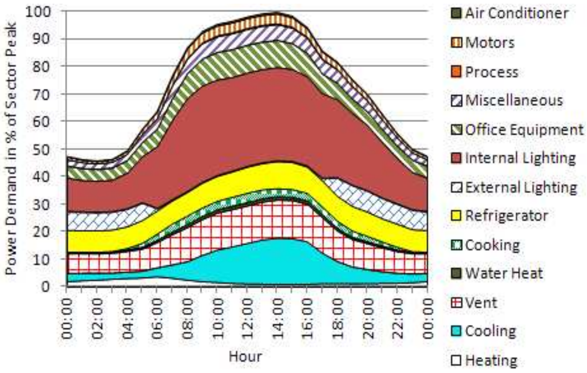

Fig. 2. Decomposed load curve in load types of commercial sector

Conversion from load types to load categories

The available statistics on electricity consumption generally divides load into load types on the basis of actual tasks performed in the end users' facilities. However, according to [3] and performed computer simulations, some appliances such as refrigerators, cooling and air conditioners have very similar real power dynamic characteristics (after initial demand, i.e., value of real power before system disturbance, is normalized to 1 p.u.). As a result, in the demand modelling process, a load category based DDLC can be developed, which divides the load according to the dynamic responses rather than end-user functionality. This way of classification not only reduces the quantity of clusters and alleviates the computational tasks that need to be executed in load model development process but also ensures the accuracy of the model.

Typical load categories

The majority of different types of loads can be divided into following load categories:

- Directly-connected induction motors (IM)
- Drive-controlled motors
- Resistive load
- Power electronics/ switch-mode power supply (SMPS)
- Lighting
- Distributed generators/micro-generation

Load type to load category conversion

The conversion from load types listed in Fig. 2 to load categories defined above is summarised in Table I. As the definition of miscellaneous devices varies from source to source [4, 7], they are classified into a single category in this paper.

Table I
ATTRIBUTION OF LOAD TYPES TO LOAD CATEGORIES
(SUMMARISED ACCORDING TO INFORMATION FROM [3])

Load Categories	Load Types
Directly-connected IM	Air conditioner, motor, process, refrigerator, vent, cooling
Resistive Load	Cooking, water heat, heating
Power Electronics/SMPS	Office equipment
Lighting	Internal lighting, external lighting
Miscellaneous	Miscellaneous

DDLC based on Load Categories

Following classification rules given in Table I, load-category-based DDLC is created as shown in Fig. 3. From this figure, types and contributions of different load categories to total demand for commercial load sector can be determined. Consequently, the commercial load sector is divided into five categories, which is much less than the original thirteen load types used in Fig. 1. If dynamic load modelling of commercial sector is to be performed now, since signatures of individual load categories are known, dynamic response of demand at any specific time can be estimated by combining individual load category responses conditioned by appropriate weighting factors derived from Fig. 3.

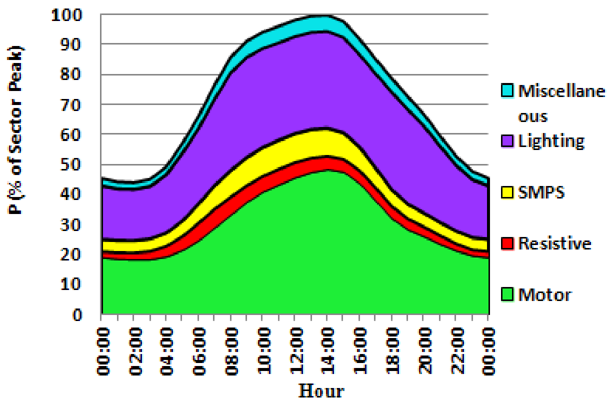

Fig. 3. DDLC based on load categories for commercial sector

Similar to the approach illustrated for commercial load sector, deterministic DDLC for other load sectors can be derived. With deterministic DDLC developed for other load sectors and considering mix of load sectors at the network bus, e.g., as shown in Fig. 4a) [4], deterministic DDLC for the overall demand at network bus can be derived as shown in Fig. 4b). As Fig. 4b) involves load categories for the overall demand, including industrial load sector, induction motors (IM) category is further split into small motors and large motors, representing residential-commercial IMs and industrial IMs, respectively.

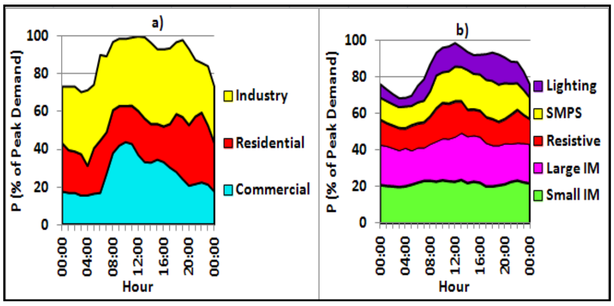

Fig. 4. Close to real time: a) load class mix, and b) load category mix at a bus

PROBABILISTIC DDLC

Once the groups of demand data for different load types are collected and corresponding deterministic DDLC created, the uncertainties in participation of different load categories should be considered. These uncertainties are result of insufficiently accurate data about participation of particular load category in total demand and variation in deployment of different end-user devices at different times. Therefore, load category participation in total demand should be represented stochastically.

Uncertainty of demand of single load sector

DDLC of Fig. 3 was produced based on corresponding data provided in Fig. 2 and normalized with respect to peak demand. In order to account for mentioned uncertainties the DDLC of Fig. 3 is produced for each set of data used for producing corresponding Fig. 2 and normalized with respect to peak demand. Different DDLC produced in this way are overlapped as shown in Fig. 5 for SMPS load category as an example. It is found that daily demands for individual load categories at different times are not completely overlapping. The corresponding maximum and minimum values of each obtained curve (example for SMPS load category is shown in Fig. 5) at any given time are connected to establish the area of uncertainty and the corresponding average value at each point in time is calculated.

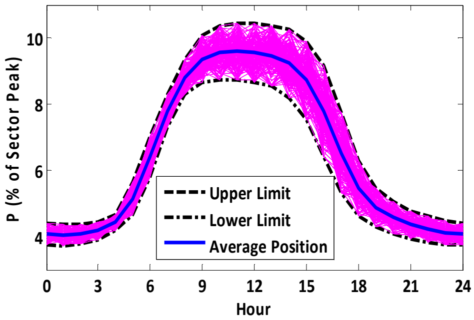

Fig. 5. 200 groups of daily loading curves for SMPS load categories in commercial load sector

After these curves have been established for each load category, they are superimposed on each other to create probabilistic DDLC shown in Fig. 6. It is observed that apart from different load categories represented by different colours, the clear deterministic segmentations shown in DDLC in Fig. 3 by solid black line are replaced in Fig. 6 by patterned areas which indicate the uncertainty of load contribution. The solid line inside the uncertainty area represents the average value of individual load category contribution. The dashed lines which bound the uncertainty areas are the upper and lower limits of individual load category contributions.

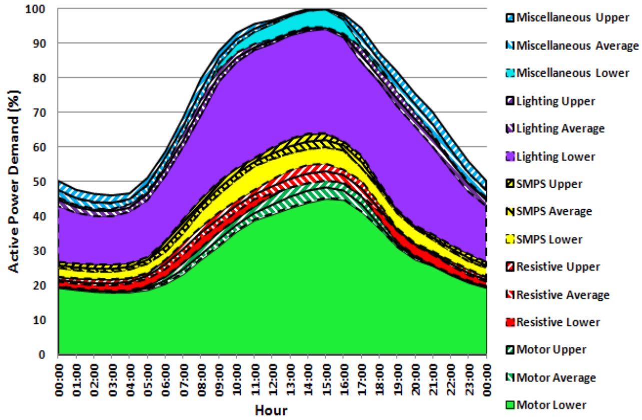

Fig. 6. Probabilistic DDLC based on load categories for commercial sector

The average value and the standard deviation of participation of each load category, given in percentage of sector peak demand, are calculated from sampled data and plotted in Fig. 7. The mean value of participation for all load categories can be read directly from the figure as well as corresponding standard deviations. The standard deviations depend on both the mean demand and the width of the uncertainty areas at different time, which reflects the trend of the fluctuation in different load category contributions.

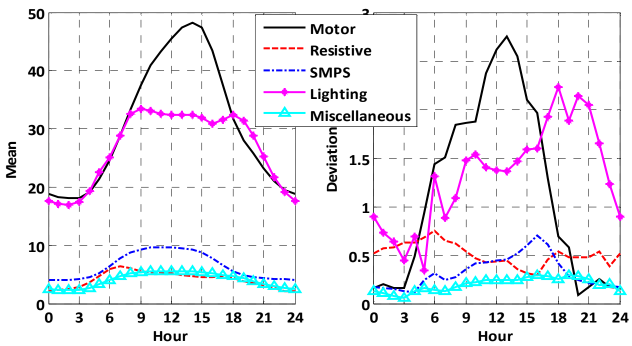

Fig. 7. Mean and standard deviation of demand for different load categories in commercial load sector

UNCERTAINTY OF THE OVERALL DEMAND

Similar to the case of individual load sector, probabilistic DDLC of the overall demand are developed based on deterministic DDLC shown in Fig. 4b). Different sets of DDLC, like one shown in Fig. 4b), are created from different sets of demand data for end-users in different load sectors and corresponding “load mix” curves shown in Fig. 4a). The resulting probabilistic DDLC developed for a network bus is shown in Fig. 8. The notation in this figure is the same as that in Fig. 6 except for the IM category, which is split in two groups (small and large motors) as before.

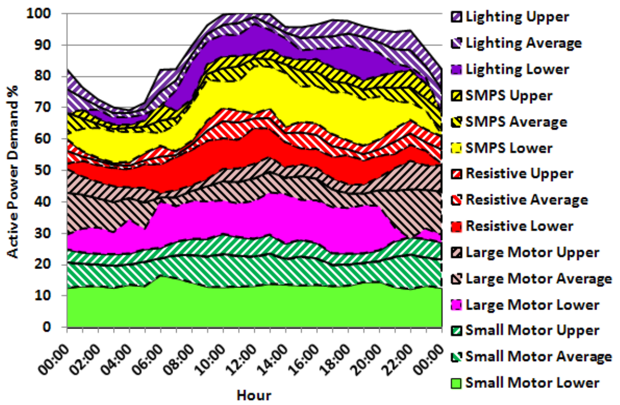

Fig. 8. Probabilistic DDLC for overall demand

The mean value and the standard deviation of contribution of different load categories to overall demand are plotted in Fig. 9. As the participation of different load categories in the overall demand at different times is more variable than in the case of individual load sector, their mean value curves have different shapes (from being reasonably smooth during the day to experiencing single or double peak) and the standard deviations are generally larger.

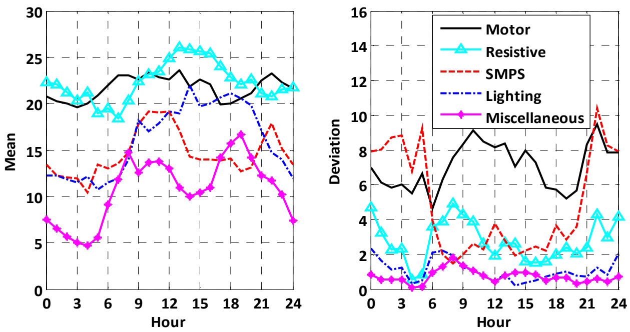

Fig. 9. Mean and standard deviation of demand for different load categories for overall demand

CONCLUSIONS AND FUTURE WORK

Due to the uncertainty caused by customers’ operation habits and the introduction of new types of devices, it is difficult to accurately predict the participation of different load categories in different load sectors and even more so in the overall demand at bulk supply point. This paper introduces the methodology for developing probabilistic decomposed daily loading curves that will facilitate more accurate estimation of dynamic response of demand to network disturbances at any given time and ultimately shaping of demand response (through corresponding demand management actions) to ensure network stable operation.

Based on available sets of demand data, the deterministic DDLC are developed first and then are converted to probabilistic curves. The probabilistic DDLC provide information on the average contribution of different load categories and possible ranges of this contribution at any given time. The degree of uncertainty in contribution of individual load category is given by the width of the uncertainty area shown in the DDLC. Developed probabilistic DDLC can, and will be used together with the corresponding dynamic signatures (characteristic dynamic responses to network disturbances) of individual load categories to estimate probabilistic dynamic response of demand (real and reactive power) to network disturbances at bulk supply point.

The probabilistic nature of the study enables close to real time prediction of demand response as well as corresponding demand response shaping and such more reliable demand side management and more secure network operation.

ACKNOWLEDGMENTS

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REFERENCES

[1] R. E. Brown and J. G. Koomey, 2003, "Electricity use in California: past trends and present usage patterns," *Energy Policy*, vol. 31, 849-864.

[2] WECC. Load Composition Data [Online]. Available: http://en.sourceforge.jp/projects/sfnet_lcm-data/downloads/loadcomposition-excel-1_7_8.zip/

[3] CIGRE, 2012, *Modelling and aggregation of loads in flexible power networks*, Working Group C4.605, Rep. 5.

[4] L. Dittmar, 2006, *Intergration of energy saving technologies and learning curves into the basic model of regional electricity liberalisation*, Diplom-Wirtschaftsingenieur, Dept. Elect. Eng., University of Flensburg, Germany.

[5] ADEME, CCE, and CRES, 2002, *End-use metering campaign in 400 households of the European Community-assessment of the potential electricity savings*, Commisson of the European Communities.

[6] R. Stamminger and R. Friedrich-Wilhelms, 2008, *Synergy potential of smart appliances*, University of Bonn, Bonn, Germany.

[7] L. Du, D. He, Y. Yang, J. A. Restrepo, B. Lu, R. G. Harley, *et al.*, 2012, "Self-organizing classification and identification of miscellaneous electric loads," in *IEEE PES General Meeting, San Diego, CA USA*, 1-6.