19th Symposium IMEKO TC 4 Symposium and 17th IWADC Workshop
Advances in Instrumentation and Sensors Interoperability
July 18-19, 2013, Barcelona, Spain

Power Profile Generator for the Test of Microgrid Measurement and Control Systems

M. Bertocco, G. Giorgi, C. Narduzzi

Università di Padova, Department of Information Engineering, via G. Gradenigo, 6/b, I-35131 Padova, Italy
ph.: +39 049 8277500, fax: +39 049 8277699, e-mail: {matteo.bertocco, giada.giorgi, claudio.narduzzi}@unipd.it

Abstract-Testing the behaviour of a microgrid measurement and control systems for responsiveness, dynamics and control capability assumes great importance to ensure the ability to meet energy demand by local distributed energy resources. The proposed work describes the design of a power profile generator that synthesises appropriate power demand inputs to test the behaviour of microgrid measurement and control algorithms.

Keywords-microgrids, power demand profile, random processes.

I. Introduction

Although smart grids originated in the world of high-voltage transmission, the concept has quickly expanded to the domain of power distribution, ultimately progressing into the idea of smart microgrids. A key target is to allow renewable energy sources to increase their share of electric energy supply. Microgrids emphasise this notion and operation as islands, at least temporarily unconnected to the power grid, is considered possible [1]. However, local response to energy demand will be conditioned by the availability status of distributed energy resources (DERs). If demand variations are to be primarily met by local sources and/or storage, measurement and control need to play a much more significant role.

Smart grids are among the best-known examples of the Internet-of-Things (IoT) paradigm where ICT technology is applied to a physical system, such as the electrical grid, to achieve greater flexibility, adaptability and improved energy efficiency. However, such benefits should not come at the expense of the availability and reliability of electric energy supply, which are taken for granted with current grids. This sets ambitious targets to the design of microgrid measurement and control sysems, particularly when distributed implementations are considered.

The study of measurement and control in smart microgrids is faced with two kinds of problems: on one hand, the present observability of electrical networks is often poor on the distribution side, even so-called smart meters typically providing just active power readings and the support for management of billing policies. Additional measurements are needed, but it is still not always clear which quantities should be considered, where measurements need to be taken and at what cost they could be provided.

On the other hand distributed control algorithms (e.g., consensus algorithms), that currently attract much interest in the scientific community, exhibit their own dynamic behaviour, that may partly depend on the features of the communication network serving the distributed control entities. As elements in the electrical grid also have a dynamic behaviour of their own, interaction between the two systems is clearly a focal point.

The integration of DERs, including energy storage, and the introduction of demand response (DR) policies at the microgrid level require a rather aggressive attitude in control and management. In this scenario, microgrid control functions will have to ensure the stability and reliability of the grid and effectively deal with demand peaks that could be considered large in a purely local perspective. This raises a number of design issues related to service availability (which is typically expected to be quite high), the use of local energy storage, load shedding, etc. Testing the behaviour of a microgrid Distribution Management System (DMS) for responsiveness, dynamics and control capability thus assumes great importance and creates challenging problems.

The test of a distributed measurement and control system by purely hardware test benches is often impractical, but the features emphasised above can be extensively characterised by providing appropriately synthesised input stimuli. The effectiveness of this approach is critically dependent on the capability to reproduce realistic power demand profiles for each node in an electrical distribution network, by means of a suitably designed profile generator which becomes, to all purposes, a dedicated test tool.

The design of a mathematical model for electrical power demand is a complex task, made difficult by the large number of variables potentially involved in the problem and by the limited availability of suitable experimental data for model validation. In the past several experimental studies were aimed at providing information for the implementation of energy efficiency policies [2], [3]. Usage data were often averaged over relatively long time intervals, thus hiding the short-term variability that is of interest here [4]. Energy consumption data are commonly divided by classes of home appliances. Nevertheless, experimental data at these aggregation levels are often the only ones available in open access reports. More recent works on modelling energy demand include the presence of DERs and consider suitably high-resolution time scales [5], [6]. However, such models appear to be too complex for the purposes of this work, as they are designed to analyse issues in energy efficiency technologies, the effects of pricing, as well as customer behaviour aspects.

This paper presents the development of a power profile generator designed to provide typical demand patterns for a microgrid-sized area, supporting the test of DMS measurement and control algorithms. Different demand aggregation levels are addressed, allowing to define patterns down to a single appliance, but also to synthesise the power demand profile of wider aggregations by means of efficient statistical models. The emphasis of the work is on the ability to reproduce both average trends and local variability, with the aim to support the analysis of reliability in microgrid DMS control algorithms.

II. The modelling problem

It is a well-known fact that user behaviour in the Internet creates peculiar usage patterns. These are generally characterised by much wider variability on lower-capacity links, whereas service demand aggregation on higher-level connections results in a sort of averaging effect, that leaves only general trends clearly perceivable. Unsurprisingly, a similar behaviour can be noticed when the electrical grid is analysed over different service areas: in fact, in service demands pertaining to electrical energy as well as to network communications, human behaviour is largely responsible for both individual variability and general trends.

In a traditional grid environment, short-term variability would be averaged out as the demand reaches large generation utilities. Thus, at the level of large power generation plants and transmission grids, normal operation is characterised by comparatively slowly-varying power demand profiles where daily, weekly and seasonal trends dominate. The use of reporting rates in the range of several readings per second for the phasor measurement units is largely dictated by fault protection and stability control requirements.

A microgrid is at the lowest level of the grid hierarchy, hence the number of end-users it serves is comparatively limited. Although this means average power demand is lower, relative variability can be much greater than in transmission systems. In fact, energy demand aggregation effects are limited and, consequently, the possibility that superposition of individual behaviours occasionally results in significant demand variations is not ruled out. Thus, demand in a microgrid is rather less predictable in the short term and could be subjected to larger relative fluctuations.

In its most general form, a smart microgrid can be seen as a group of “energy nodes”, including passive and active loads, distributed generation units (e.g., photovoltaic (PV) arrays, small wind or water turbines) and local energy storage units, connected to a common local grid. This arrangement might correspond, for instance, to a neighbourhood comprising homes, public buildings and small industrial settlements. Modelling the power demand profiles of such heterogeneous environment requires a clear understanding purposes and limits.

The interest in modelling power demand profiles at the microgrid level follows from the fact that local energy supply capability provided by DERs might be somewhat limited. Particularly with a view on possible islanded operation, this increases the importance of thoroughly testing microgrid measurement and control algorithms. Assessing reliability, however, requires characterising the system with respect to statistically extreme events, which may be difficult or even dangerous to reproduce in a physical test set. This is the main motivation for the power profile generator discussed in this paper and allows to clearly identify the essential features of the design.

In a small neighbourhood it could be possible to consider some of the larger energy users individually and characterise them by well-defined demand patterns. This is the case with industrial activities and, to a lesser extent, some public buildings, which are likely to be present in limited numbers, but can account for a significant proportion of demand. For these units it would also be comparatively easy to determine the fraction of the resulting load that can be considered dispatchable. DERs could also be assumed to have reasonably uniform behaviours, allowing to use a limited set of standard models. Weather could be assumed to be nearly uniform in the area covered by a microgrid so that, for instance, illumination for PV panels would be the same at least on average.

Once DERs and the few larger consumer units have been accounted for, the profile generator task is to provide a simple but realistic representation of the collective demand profiles for the variety of heterogeneous consumer units that make up the rest of the microgrid environment. In doing so, particular care has to be devoted to the ability to correctly reproduce demand variability in the short term, including extreme values, its statistical distribution and the way it can vary along the day. It should be mentioned that energy generation could also take place at the same locations (so-called *prosumers*), but the two aspects are better modelled separately.

For the most part energy consumers would be a mix of shops, small offices, workshops, houses and flats. These consumer units would be too numerous to describe individually, yet the variability of energy demand patterns can be large enough to warrant specific consideration, particularly in view of the much limited smoothing effect that can be obtained at this low level of demand aggregation.

One of the difficulties lies in the fact the each individual consumer unit is itself formed by a mix of appliances having different usage profiles, which can depend both on the nature of the appliance (e.g., refrigerator, PC, lighting) and on individual user habits. Furthermore, the use of some appliances almost uniformly peaks in some parts of the day (e.g., television sets in houses) and might even give rise, occasionally, to the electrical equivalent of a computer network flashcrowd effect. The use of other kinds of appliance can be more closely related to individual habits and the distinction between dispatchable and non-dispatchable appliances may as well reflect personal needs or preferences (e.g., deferred start in washing machines).

Since the driving motivations for the development of existing power demand models are mainly related to energy policies, such models are hardly suited for the aims of this work. Although studying them proved useful, the power profile generator presented in the next sections follows a different approach, which owes much to the already mentioned similarity with Internet usage patterns.

III. Generator design and validation

A power profile generator is necessarily the result of a tradeoff between the desire for accuracy and the need for underlying models to be concise. In this work two features were considered essential: the ability to produce significant short-term time variations and the possibility of creating large, worst-case demand peaks. These requirements are related to the intended target of testing management and control in a microgrid.

The adopted modelling approach allows to define power demand at two different levels: the *appliance level* provides for a very fine tuning of power profiles but is also resource-consuming, as it requires the definition of specific appliance usage patterns and appliance mix for each end-user. The *end-user level* relies on a stochastic model based on chaotic maps to generate an aggregated power profile with realistic short-term time behaviour and peak-to-average characteristics. Eventually, appliance level analysis was found useful as a preliminary step that helped validate the statistical features of end-user level profiles.

As the target is the creation of realistic inputs for stimulus-response testing of microgrid control algorithms, simple models applicable as well to the behaviour of Internet users are employed as the starting point in the reproduction of time-varying power profiles. In principle, these models are considered to describe the desired short-term variability well enough. The main effort will be in matching their features to available statistical data on energy demand.

A. Appliance-level power profiles

This part of the study considers the modelling of individual appliance types. The two main features are the usage pattern, that determines the time distribution and intensity of switch-on requests, and the length of switch-on times. With regards to these, appliances can be divided into:

- devices with independent regulation and repetitive switch-on cycles (refrigeration, air conditioning);
- devices with user-activated pre-defined operation cycles (e.g., washing machines);
- user-activated devices (e.g., lighting).

Power demand related to user-activated appliances depends on human activity within an individual consumer unit. This can be described, for instance, by a Markov chain model [5], however, for the purposes of a control system it suffices to assume that events occur in an essentially random way. To a first approximation, activation times are considered independent of each other, so that in the short-term a stochastic Poisson process with constant intensity λ can adequately describe the situation. Hence, the time intervals between consecutive activations of an appliance are described by an exponential probability distribution of the form $e^{-\lambda t}$.

For independently-activating devices, short-term power demand could be described even more simply by a Bernoulli process with a given activation probability *p*, however a Poisson process with an appropriately set intensity is equally effective and was preferred in the interest of uniformity.

Depending on the nature of the appliances, model parameters can be varied to account for daily and weekly cycles related to user behaviour and for other changing conditions (e.g., weather or season). Testing microgrid management and control under critical situations may in fact require to account for longer term variations, which justifies the need to include them into the model. With a Poisson model, this can be obtained simply by considering a variable intensity, so that the probability of an interarrival time having length Δt is:

$$e^{-\lambda(\tau)\Delta t} \tag{1}$$

Since intensity $\lambda(\tau)$ varies slowly compared to the time step considered in the model (which is usually one minute), simulation can proceed by a quasi-stationary succession of steps and does not actually require to tackle the problem of reproducing a non-homogeneous Poisson process.

To complete an appliance model, power states also need to be defined, including standby power and, where applicable, the range of power values in the "on" state. It may also be useful to define reactive power demand (e.g., for workshop machinery, such as lathes and mills). Finally, the duration of the active state can be either fixed, or defined within a range. When a range is considered, actual values for each activation are randomly drawn from an associated statistical distribution, experience showing that a uniform probability density function suffices for the modelling purposes considered in this work.

By varying a comparatively simple set of parameters, this model can describe the power demand of different appliance classes. A difficulty lies in the need to determine how intensity $\lambda(\tau)$ varies: in most cases it follows appliance-specific daily patterns, for which information can be drawn from existing studies. Fig. 1 shows as an example the result of matching a Poisson-based model for TV sets power demand to consumption data presented in [2]. The initial discrepancy is due to the simulation start transient.

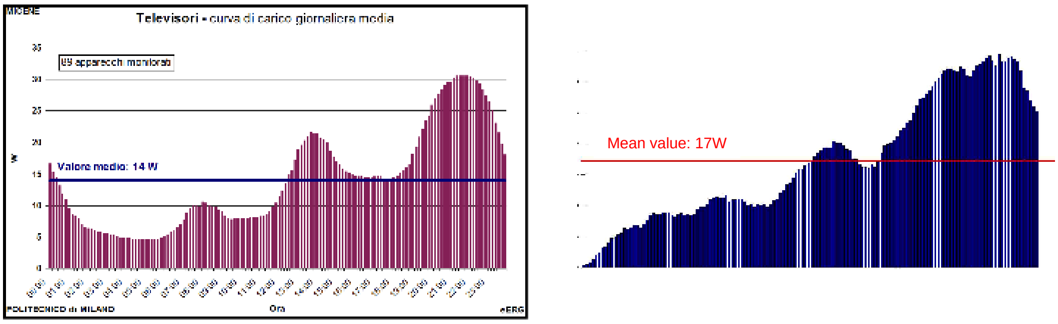

Fig. 1: (left) measured mean daily power demand for TV sets [2]; (right) matched Poisson-based model.

B. Power profiles at the end-user level

Control functions in a microgrid help manage local demand variations by sending suitable control inputs to inverter-based DERs. To test control algorithms, it is preferable and simpler to consider the power demand profiles of end-user consumer units, or their aggregation into suitably sized *end-user clusters*, rather than work at the appliance level, since details would be too complex, except for a few special cases. A logical progression from what has been discussed above could be the aggregation of a suitable number and variety of appliances. However, this is a cumbersome process and has the disadvantage that, on average, it tends to smooth out demand peaks. In different words, although the resulting end-user level profile appears realistic, it tends to de-emphasise extreme events, which are instead the main concern in reliability analysis.

To reproduce the desired wide variability in a simple way, end-user level power profiles can be generated by means of a statistical model employing a chaotic map. The idea is borrowed from the computer network world, where the use of an *intermittency map* to generate ON/OFF times for sending data packets was proved to be effective [7]. Power demand can be seen to feature similar patterns of human-related statistical variability.

A chaotic map is a one-dimensional map whose time evolution is described by a state variable x_n. The value of x_n changes over time according to a non-linear relationship. The map employed for this work is:

$$x_{n+1} = \left\{ \begin{array}{lll} F_1(x_n) = x_n + (1-d)\left(\dfrac{x_n}{d}\right)^{m_1} & \text{for: } 0 < x_n \leq d & \text{that is: } y_n = 0 \\ F_2(x_n) = x_n - d\left(\dfrac{1-x_n}{1-d}\right)^{m_2} & \text{for: } d < x_n < 1 & \text{that is: } y_n = 1 \end{array} \right\} \quad (2)$$

where m_1, m_2 and d are the map parameters. The *indicator variable* y_n determines whether the state corresponds to an OFF (y_n = 0) or ON (y_n = 1) condition, the respective probabilities depending on the map parameter d, while the other two parameters influence the statistical properties of the resulting random process.

Chaotic map calculation (2) is iterated for a number of times during each interval defined in the power profile, the total count of ON outcomes within that interval providing the corresponding power demand from active appliances of the modelled user cluster. This analytical model is able to concisely represent variability characterised by occasional large demand peaks, since the generated process has a statistical property known as long range dependence, which implies the possibility of strong correlation between events widely separated in

ISBN-10: 84-616-5438-2 | ISBN-13: 978-84-616-5438-3

time.

The use of chaotic maps allows simple generation of power profiles that, by careful tuning of parameters, can be matched acceptably well to experimental profiles, obtainable from several reports published in recent years. In this case, matching of the model to longer term trends can be obtained by making the parameter *d* time variable.

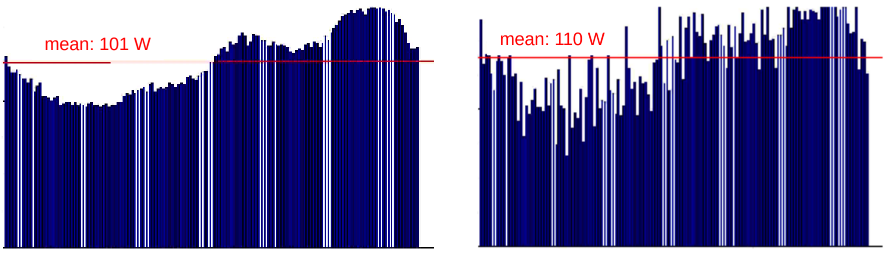

Fig. 2: (left) aggregated power demand from a set of appliances [2]; (right) matched chaotic map model.

In the example of Fig. 2, the power profile generated by the chaotic map has been matched, by determining the time varying function $d(\tau)$, to the experimental profile obtained by the aggregation of consumption data referred to a set of different appliances [2]. It is important to note that, while the general trend is similar, the chaotic map model emphasises short-term variability, as desired. Equation (2) thus provides a simple mechanism to generate input stimuli to a control algorithm, with a simulation time step set to one minute. Changes in average demand are determined by varying the threshold $d(\tau)$, which again varies slowly compared to the simulation time step.

Matching a model to experimental data can be made difficult by the absence of information specific to the microgrid environment under analysis. Once the feasibility of matching the end-user level chaotic map model to experimental data has been proved, it could be more useful to adopt a two-step process, where end-user data are in turn obtained by the aggregation of appliance level models. It is reasonable, in fact, to assume that by variously combining a limited set of carefully validated appliance level models, the different varieties of consumer units can be synthesised.

To validate this approach, two chaotic map models were generated and matched, respectively, directly to experimental data and to end-user data synthesised by aggregation of appliance level data. The resulting profiles were compared by calculating the normalised variation factor (NVF) [8]:

$$NVF=\frac{\sum_{i=1}^{N}\left[P_{mod}(i)-P_{meas}(i)\right]^2}{N\left[\frac{1}{N}\sum_{i=1}^{N}P_{meas}(i)\right]^2} \tag{3}$$

that represents an indicator of model average goodness of fit.

The process was repeated for ten simulations, computed NVF values being reported in Fig. 3. It is interesting to note that, even though model tuning from appliance level models is less accurate, the discrepancy remains in the region of 3%, as opposed to 2% when the chaotic map model is directly matched to experimental data.

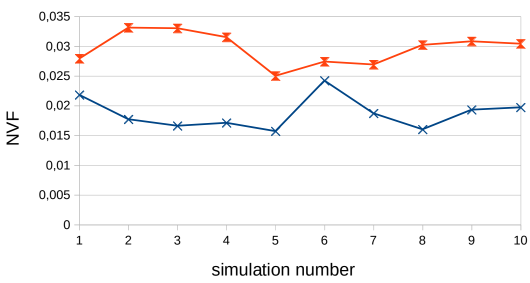

Fig. 3: normalised variation factor for chaotic map model matched directly to experimental data (crosses) and to an aggregate power profile obtained from validated appliance level models (double triangles).

IV. Conclusions

Characterising a test tool such as the power profile generator presented in this work is difficult, unless experimental data acquired for the same purposes are available. Unfortunately, this is hardly the case and it becomes necessary to translate the generator outputs and aggregate them to enable comparisons with data from published reports. The process is challenging and, inevitably, does not allow to check and validate the tool in detail. Nevertheless, profiles can be tuned to reproduce correct power demand levels for a given end-user cluster.

Statistical variability, essential to suitably stimulate the microgrid DMS inputs, is introduced by the nature of the chaotic map itself and can be controlled by map parameters. Furthermore, the generated random process is known to have statistical properties such as long-range correlation and a heavy-tailed probability density function, which lead to the occasional generation of power demand peaks, resulting in a useful stress-test for the microgrid control algorithms.

To the best of our knowledge, this kind of power profile generator represents a novel approach, which could provide useful support to the test and qualification of microgrid-oriented measurement and control systems.

Acknowledgement

The authors wish to thank ing. Tiziano Baietta for his contribution to the preliminary discussions leading to this work and for his invaluable help in the validation of appliance and user-level models.

References

[1] N. Hatziargyriou, H. Asano, R. Iravani, C. Marnay, “Microgrids”, *IEEE Power and Energy Magazine*, vol. 5, pp. 78-94, 2007.
[2] F. Di Andrea, A. Danese, “MICENE – Misure dei consumi di energia elettrica in 110 abitazioni italiane – Curve di carico dei principali elettrodomestici e degli apparecchi di illuminazione”, end-use Efficiency Research Group, Politecnico di Milano, 2004.
[3] P. Bennich, A. Persson, “Methodology and first results from end-use metering in 400 Swedish households”, in: Proceedings of EEDAL 06 International Energy Efficiency in Domestic Appliances and Lighting Conference, Gloucester, UK, 2006.
[4] A. Wright, S. Firth, “The nature of domestic electricity-loads and effects of time averaging on statistics and on-site generation calculations”, *Applied Energy*, 84 (2007), pp. 389-403.
[5] J. Widen, E. Wackelgard, “A high-resolution stochastic model of domestic activity patterns and electricity demand”, *Applied Energy*, 87 (2010) , pp. 1880-1892.
[6] I. Richardson, M. Thomson, D. Infield, C. Clifford, “Domestic electricity use: A high-resolution energy demand model”, *Energy and Buildings*, 42 (2010), pp. 1878-1887.
[7] A. Erramilli, R. P. Singh, and P. Pruthi, “Chaotic Maps as Models of Packet Traffic”, in: J. Labetoulle, J. W. Roberts, *The Fundamental Role of Teletraffic in the Evolution of Telecommunications Networks*, Elsevier, Amsterdam, 1994, pp. 329–338.
[8] A. Capasso, W. Grattieri, R. Lamedica, A. Prudenzi, “A bottom-up approach to residential load modeling”,