A COMPARATIVE ASSESSMENT OF A QUASI-SEQUENTIAL AND A SEQUENTIAL APPROACH FOR DISTRIBUTION NETWORK STOCHASTIC ANALYSIS

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ABSTRACT

This paper intends to compare two different approaches for the stochastic analyses of low voltage distribution networks. A quasi-sequential approach using a distribution based method and a sequential approach using Seasonal ARMA time series for individual consumption and generation are benchmarked on a low voltage network. A qualitative and quantitative analysis of two scenarios (without and with storage) show the advantages and limitations of both approaches. Additionally, it highlights the great potential of modeling sequentially as new load management techniques will be made available.

INTRODUCTION

In the last decade, electrical grids have been undergoing a major transformation. The increasing integration of renewable electricity sources, the liberalization of the electricity sector and the development of new technical solutions are a few motives fostering this process. Mostly impacting transmission grids until recently, distribution networks are now subject to many changes as well.

Initially almost entirely passives and behaving deterministically with power always flowing in the same direction and with overall known ranges of magnitudes, distribution networks are now subject to power flows that can have a strong stochastic behavior. Due to the integration of local renewable electricity sources, fluctuations on the network can be much greater and backflows can occur when global production exceeds consumption in a network feeder. This can imply to either modify extensively the network infrastructure or operate it more dynamically in order to regulate load flows. The first solution is not feasible in the current context of low expenditures and today's large scale deployment of smart meters brings a whole new perspective for implementing dynamic solutions. Hence, load control strategies and energy storage now give potential for implementing smarter grids, and must be accurately modeled.

Another important issue raised by the increased stochastic behavior of power flows on the network lies in the new network infrastructure developments or its reinforcements. Deterministic criteria such as N-1 tend to lead to oversized solutions as they aim to prevent even the least probable network states. Economic optimum nowadays primes over the best technical solution. It can be met by minimizing the cost related to infrastructure development for reaching a certain level of reliability and the cost related to a defective functioning at customer's level associated to that level of reliability (consequences of voltage range trespassing, power interruption…).

In this context, stochastic sequential network analysis proves to be a relevant tool for new network developments and planning [1]. It relies on network state statistics which can be captured by smart meters' data. Moreover, sequential analysis makes the simulation of time dependent technical solutions effective.

In that regard, this paper aims to emphasize the relevance of such a tool through the simulation of a low voltage distribution network. Two main approaches, respectively quasi-sequential and sequential, are compared pointing out their particularities, advantages and drawbacks using Smart Meter data. Such microscopic modeling requiring solely historical data recorded by smart meters is recent [2] and this paper intends to highlight as well the potential of this mean to build effective and efficient models. Finally, the necessity to adopt sequential models in the upcoming context is demonstrated.

In the first section, the quasi-sequential and the sequential approaches are introduced along with the method used for each in this paper. Then, a benchmark based on scenarios, respectively without and with a shared storage unit, is conducted on a low voltage feeder example. A qualitative and quantitative analysis of the benchmark results is thereby discussed. The third section points out a few important considerations about the methods and discuss the possible prospects for this work.

MODELING APPROACHES

To this day, a quasi-sequential approach has shown to be sufficient for most of the problems. However, there is a growing need for models holding an accurate time correlation structure and therefore, sequential models are introduced. This section presents the two approaches.

A quasi-sequential approach: individual statistical distributions

In the framework of probabilistic load-flows, a quasi-sequential approach computes values from the quantities' distribution (electrical powers in this case) for different time steps. It is important to mention that samplings occurring for each of these time steps are strictly independent between each other and therefore cannot be

considered as a sequential representation. In that regard, the distributions of the collected prosumption (consumption + generation) data are established for each individual. In this work, we choose to calculate two Cumulative Distribution Functions (CDF) for each time step; one CDF associated to the individual power consumption and the other CDF associated to the individual power generation. Those statistical profiles are compiled for a certain time frame leading to typical day profiles, typical week profiles, typical year profiles… In this paper, we require the use of Typical Day Profiles (TDP) [3]. This compilation of statistical profiles allows to introduce some autocorrelation between subsequent time steps as they restrict the distribution of samples. Therefore, some form of sequentiality is introduced in a non-sequential representation, where from referring to a quasi-sequential approach.

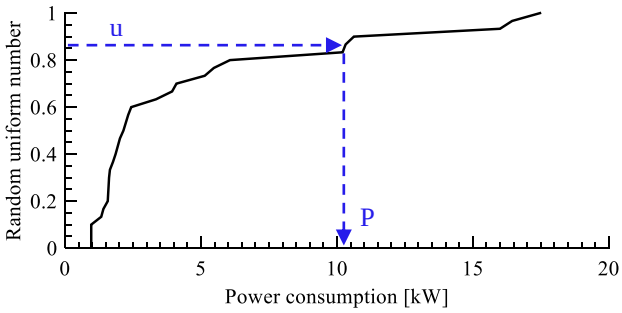

Figure 1: example of a CDF power sampling using a uniform random number for a specific quarter of an hour

A Monte-Carlo process can be initiated through sampling a large number of power values from their CDFs. Power sampling occurs simply by generating random uniform values between 0 and 1 (u), and then associating the corresponding power values (P) through the CDF (see figure 1 above).

A sequential approach: Seasonal ARMA models

Unlike non-sequential approaches, a sequential approach has the important feature of generating temporally-linked values with one model. Subsequently, each computed state is therefore dependent of the previous ones leading to a better representation of intrinsically sequential processes.

In this paper, we study the option of time series models and more particularly Seasonal Auto-Regressive Moving Average models (SARMA) [4]. This type of sequential model allows a representation of both the distribution and the autocorrelation of the data.

SARMA time series consist of an auto-regressive term reproducing the deterministic pattern over time of a variable and a moving average term holding the evolution of the disturbances called innovations through time (see details below). Additional terms are able to take into account a non-deterministic seasonality. This meets the specific needs of modeling data with both deterministic and stochastic components with seasonality.

ARMA Process. A *stationary linear process* $\{X_t\}$ is called *ARMA* (p,q), $p \geq 0,\ q \geq 0$ if there are constants $a_1 \ldots a_p\ (a_k \neq 0)$ and $\theta_1 \ldots \theta_q\ (\theta_j \neq 0)$ and a process called innovations $\{\varepsilon_t\} \square WN(0,\sigma_\varepsilon^2)$ so that:

$$X_t = \sum_{k=1}^{p} a_k X_{t-k} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad (1)$$

The first part of the equation above is the Auto-Regressive (AR) process of order p and captures the deterministic part of the series, i.e. routine consumer activity. The second part is a Moving Average (MA) process of order q and captures the stochastic part of the data. Equation 2 can be rewritten using the backshift operator $B^i X_t = X_{t-i}$:

$$\left(1 - \sum_{k=1}^{p} a_k B^k\right) X_t = \left(1 + \sum_{j=1}^{q} \theta_j B^j\right) \varepsilon_t \qquad (2)$$

SARIMA Process. Let

$$Y_t = \nabla^d \nabla_s^D X_t = (1-B)^d (1-B^s)^D X_t \qquad (3)$$

where $\{X_t\}$ is called *SARIMA* $(p,d,q)\times(P,D,Q)_s$ of seasonality s if (4) is a stationary process that follows:

$$A(B)\,F(B^s)\,Y_t = \Theta(B)\,G(B^s)\,\varepsilon_t \qquad (4)$$

where

$$A(B) = 1 - \sum_{k=1}^{p} a_k B^k,\ \ \Theta(B) = 1 + \sum_{j=1}^{q} \theta_j B^j \ (5)$$

and

$$F(B^s) = 1 - \sum_{k=1}^{P} \varphi_k B^{k\times s},\ \ G(B^s) = 1 + \sum_{j=1}^{Q} \gamma_j B^{j\times s} \ (7)$$

The two terms in (6) refer respectively to the AR and MA processes, the first term of (7) corresponds to the Seasonal AR process (SAR) of order P and the second term is the Seasonal MA process (SMA) of order Q.

More information about the methodology for the definition of such microscopic models is available in [2].

BENCHMARK

Through the following benchmarks, the relevance of stochastic analysis is highlighted together with the assessment of the TDP and SARMA prosumption representations.

Presentation

For the two scenarios studied, a 16 nodes unbalanced three-phase low voltage network is studied (see figure 2). It is an arbitrary but realistic feeder for which 15 low voltage individuals, all equipped with photovoltaic panels, are distributed among the three phases of the network.

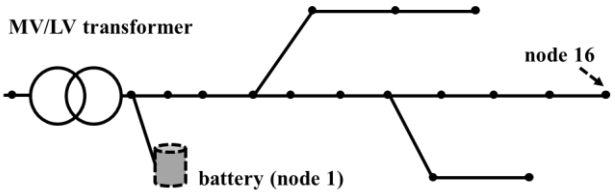

Figure 2: Low voltage network of 16 nodes studied in the benchmark

The prosumers' power consumption and generation for both quasi-sequential and sequential representations are computed using real quarter-hourly Smart Meters (SM) data. Those data were collected from a real feeder in the city of Flobecq (Belgium) as part of a pilot project. All models are established on the data of the month of August 2014, i.e. 2976 quarters of an hour. That time of the year turns out to be most interesting for studies as the photovoltaic generation is significantly higher.

Methodology

The assessment relies on the qualitative and quantitative analysis of electrical quantities and relevant computed indexes. In order to do so, a probabilistic analysis of the distribution grid, for each time step, is conducted using a Monte-Carlo framework. This approach performs a large number of simulations that compute underlying network states through a load-flow algorithm and leading to a network state distribution.

The Monte-Carlo generation of all the power consumptions and generations is performed either by sampling randomly the CDFs or by feeding the SARMA model with a random innovation term. Moreover, the sampling of all individuals' consumption is independent (no correlation between individuals for a specific quarter of an hour was established [5]) while a full correlation is applied when sampling generation data. Indeed, due to the spatial circumscription of the analysis, the correlation of the solar irradiance between the different buildings is close to unity.

It should be noted that the 15 individuals were selected out of a set of 18 prosumers. Although a reasonable model can be obtained in most cases with a SARMA approach, a satisfactory model cannot always be defined for different considerations discussed in [2]. Additionally, the performances reached for each individual are not identical. The next section discusses this consideration in more depth. Finally, the stochastic tool developed uses an efficient load-flow algorithm well suited to distribution networks [6].

Stochastic analysis of network without storage

In this stochastic analysis, the apparent power flowing through the MV/LV transformer (node 1) is first highlighted. Figure 3 shows the mean load throughout the day while figure 4 shows a few days of load evolution. In each figure, the comparison is performed between the real data (SM), the typical day profile method (QSQ) and SARMA time series (SQ).

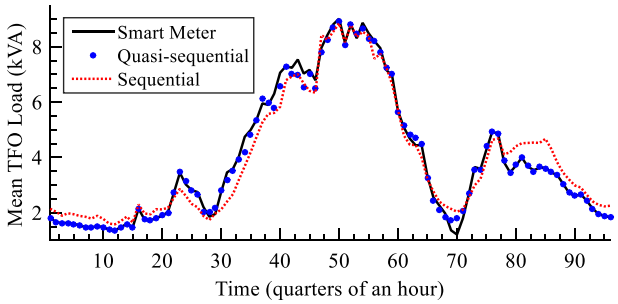

Figure 3: Mean daily apparent power load of the MV/LV transformer

It appears very clearly that the quasi-sequential approach almost fits the mean distribution. It is expected as a sufficient number of samples sweeps the whole original distribution on which it is based. As to the sequential approach using SARMA, though it does not perform comparably, it manages to reproduce the distribution fairly well.

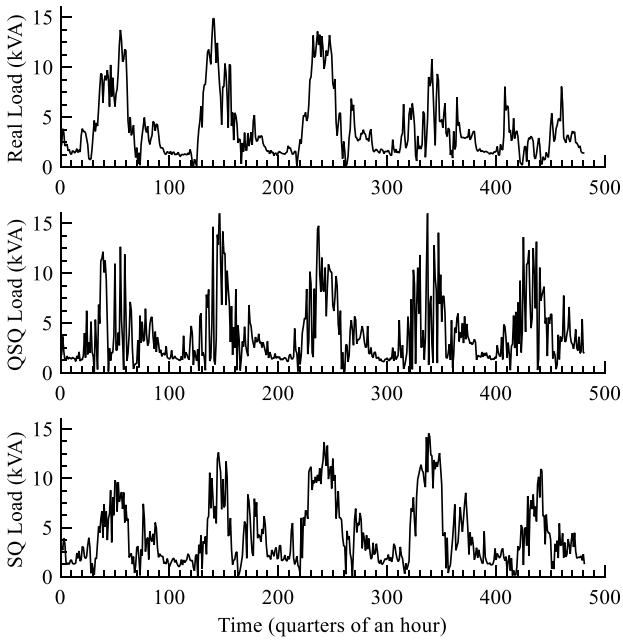

Figure 4: Comparison of the temporal evolution of a few days of the MV/LV apparent power load (upper plot: real data, center plot: TDPs, lower plot: SARMA time series)

Figure 4 shows a very different perspective when it comes to the general evolution through time. The effect of independent sampling used by the quasi-sequential approach leads to unreasonable transitions and a high general variability. The contribution of sequential models hence emerges. Indeed, similarly to the original data, it achieves to reproduce the transitions pattern much more effectively.

The qualitative observations based on figures 3 and 4 are reinforced more quantitatively by table 1 below. It depicts the probability of occurrence and the mean

duration of voltages below 227 V (a) and above 237 V (b) at node 16. The first index thus pertains to the distribution performance while the second index emphasizes the sequential performance.

Table 1: Comparison of the probability of occurrence and the mean duration of voltages under 227 V (a) and voltages over 237 V (b)

	Probability of occurrence [%]	Mean duration [quarters of an hour]
Smart Meter	6.19 (a) / 6.90 (b)	2.16 (a) / 2.63 (b)
Quasi-sequential	6.71 (a) / 6.73 (b)	1.29 (a) / 1.39 (b)
Sequential	4.83 (a) / 7.38 (b)	2.01 (a) / 2.09 (b)

As mentioned earlier, as TDPs are a distribution based method, they lead to excellent distribution performance related indexes. The SARMA approach suffers a somewhat more inaccurate distribution representation. On the other hand, although there is still some room for improvement, the SARMA approach leads to much better indexes of mean duration than the TDPs and confirms the observations previously discussed in regard to figure 4.

Stochastic analysis of network with storage

This analysis includes the presence of a battery at node 1 of the network. The battery has a 120 kWh capacity and can store or deliver up to 60 kWh per hour (a simplified linear charge/discharge curve is considered). Figure 5 below illustrates the time evolution of the battery load over a few days.

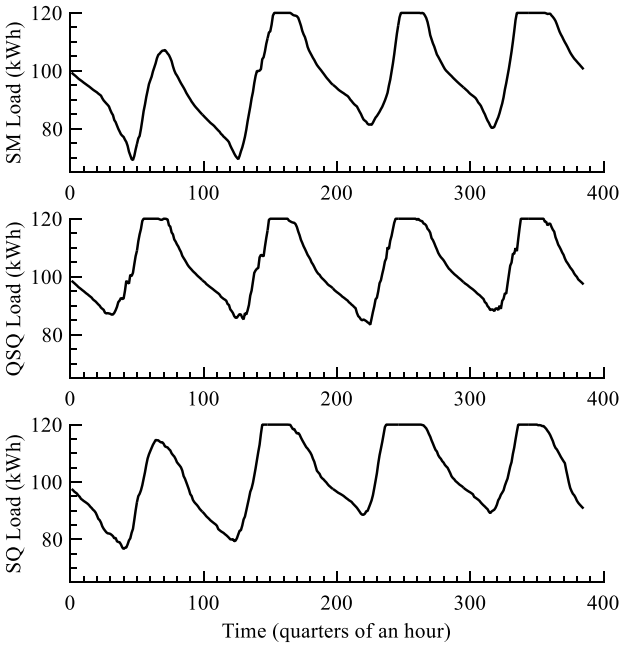

Figure 5: Comparison of the temporal evolution of the battery load over a few days

Again, some significant differences of temporal behavior can be observed. While the sequential approach succeeds in representing different patterns corresponding to days with different dynamics, the quasi-sequential approach fails to render such consideration. It just generates profiles with a similar behavior resembling much to an average profile. Furthermore, spurious charge/discharge cycles can be noticed. This consideration is emphasized hereafter.

Table 2 shows that the mean battery load is very close to the real value when using the sequential approach. Although this value depends very much on the correct distributions of power exchanges with the network, the TDP representation achieves worse results. Indeed, days with high generation of photovoltaic power lead to the maximum capacity of the battery. Consequently, some energy is forced back to the MV network and is therefore not stored. That phenomenon occurs to a lesser extent with TDPs as they reproduce almost systematically an averaged profile without such high generation. TDPs hence underestimate the amount of energy not stored.

Table 2: Comparison of the mean battery load and the mean duration charging cycle

	Mean battery load [kWh]	Mean duration charging cycle [quarters of an hour]
Smart Meter	90.91	11.25
Quasi-sequential	102.83	3.27
Sequential	90.45	10.03

The mean duration of the charging cycle (table 2) characterizes the frequency of charge/discharge cycles. As emphasized qualitatively on figure 5, the TDP approach introduce spurious charge/discharge cycles and therefore a lower duration of those cycles. This is expected as it is a sequential based index. On the other hand, the SARMA approach achieves good performances.

DISCUSSION AND PROSPECTS

This section aims to highlight some points of attention before giving a few prospects.

One consideration is the bulking effect of the power consumptions and generations resulting in a better global distribution performance and better underlying indexes. Indeed, the distribution inaccuracies tend to be smoothed with the number of individuals. Furthermore, the overall autocorrelation performances for consumption are averaged when considering several individuals. On the other hand, inaccuracies in the autocorrelation of the generation representations are multiplied as they are sampled with a full correlation.

Besides, the diversity of photovoltaic generation profiles is considerable. Indeed, they are subject to "regimes" depending mostly on the cloud cover of the day (sunny, cloudy, covered…). Different dynamics are therefore at stake and a single model tends to average those. This remark can be made for the consumption pattern as well but for different reasons (see [2]). Sunny days lead to a quasi-deterministic bell shaped curve. The stochasticity inherently introduced by SARMA models cannot reproduce such days of very high and constant generation. Therefore, overvoltage duration indexes are inclined to be underestimated. This can be noticed in the results exposed as August count many sunny days. Generally speaking, considerations involving considerable deterministic components introduce underestimation in sequential indexes as well.

SARMA time series lack precision in the distribution rendering. The methodology is currently being adapted in order to integrate the distribution based method in the framework of SARMA representation. The first results are promising.

Modeling accurately such complex data as prosumption with only one model is illusory. Henceforth, different regimes with different dynamics could be modeled separately and be linked using a Markov chain. Moreover, different approaches could be considered. For example, a deterministic model for sunny days would be better suited. Besides, other time series methods or machine learning techniques are being currently investigated.

CONCLUSION

The profound changes in the context of the low voltage networks force system operators to develop more active operation schemes. In addition, new network system planning should include those new considerations as well if investments are to be limited.

Stochastic analysis demonstrates the capability to handle the growing random component of the network behavior inherent to the integration of distributed generation. Furthermore, active management technique such as load shifting require using a sequential representation.

In this paper, two modeling approaches for stochastic analysis were presented and assessed. A quasi-sequential approach using a distribution based representation (typical day profiles) and a sequential approach using Seasonal ARMA time series were used to model the consumption and generation of 15 individuals on a low voltage feeder. The tool used for this work was developed with an effective load-flow algorithm in a Monte-Carlo framework.

It turns out that sequential models complete more realistic temporal evolutions as they can reproduce the autocorrelation pattern. Although, some improvements to the method should be developed in terms of distribution and sequential performances, sequential models prove to be essential for the new applications found on low voltage distribution networks. Storage solutions and more generally load management strategies can be simulated correctly only with time coherent series. In the near future, the development of improved sequential models should therefore prove to be the most efficient way to tackle the many new operational and planning challenges to come.

MISCELLANEOUS

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