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Dynamic Load Parameter Assessment Based on Continuous Recorder Measurements

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***Abstract*—This paper proposes an original approach to assess the parameters of a dynamic load model. By taking advantage of continuous recorder measurements, the procedure can be fully automated. The idea is to exploit natural voltage variations caused by transformer tap changes. These variations are detected by a robust event detection algorithm. To deal with the huge stochastic variation of the load, an averaging process is used and its output is used in a nonlinear identification algorithm. Results given by this procedure on real measurements taken in a substation in the Belgian power system are shown. A review of the literature on load model and on parameter identification approaches is also presented, allowing a better understanding of the aim of the procedure developed.**

***Index Terms*—Load modeling, nonlinear dynamic load model, automatic assessment.**

I. Introduction

The loads are probably the least known element of the power systems. Their behavior changes during the day – peak vs. based load – and during the year – winter vs. summer load. Considerable differences can also be observed depending on the type of load: industrial, services or residential. Rough estimation can be found in international surveys [1], [2] but they present important variations and might not be accurate enough for some applications.

All simulation-based applications can benefit from improvement of the load model: load-flow, contingency analysis, dynamic security assessment, simulations for protective devices... The needed accuracy is different for each case. If a constant power load model gives good results for a load flow, it would give a completely inadequate prediction for dynamic security assessment in a voltage stability context. In the same way, simulations to assess the angular stability (small signal or transient) can give very different conclusions depending on the used load model [3].

A better knowledge of the load model for the dynamic simulations of the power system is thus required. This paper will present a new automated approach that can give the parameters of a dynamic load model. First of all, section II gives a classification of the existing load models and section III summarizes identification approaches. These two sections help to understand the aim of the methodology described in section IV. Section V shows results with field measurements taken in a substation of the Belgian power system.

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II. Load models

A wide range of load models have been described in the literature. Several classifications in categories can be made. The first two are very common and are found in nearly all papers on load modelling. However it is interesting to go one step further and to clarify other categories that are often only suggested.

A. Component-based vs. measurement-based model

Two very different approaches can be used to build up a load model. The component-based approach starts from individual components to obtain an aggregated response of the load at higher voltage level. The measurement-based approach uses measurements taken directly at this higher voltage level to fit the parameters of a model, without other knowledge of the composition of the load.

Each method has its own advantages. The component-based approach allows a better *generalization capability*. Only the load mix of each bus – i.e. the proportion of industrial, residential and service load – is required to compute a relevant load model for the whole system once behaviour of each classes is known [4], [5].

This generalization process cannot be used with the measurement approach. When the load model parameters of one bus have been determined by field measurements, no information about the validity of this model for other busses is available. Measurements should thus take place at each bus where the load must be modelled.

The main advantage of the measurement-based approach is its limited need of data. It does not require any data about the load composition. That can be a major advantage in a liberalized market where the data about load composition belongs to the distribution system operator while the transmission system operator tries to build a model of the load.

B. Static vs. dynamic load model

A static load model is a model where the power is function of the voltage and/or the frequency but without time dependency. The ZIP load model is an example which is widely used. It shows three terms, capturing the behavior of a constant power, constant current and constant impedance load.

$$P = P_0\left(a_1\left(\frac{V}{V_0}\right)^2 + a_2\left(\frac{V}{V_0}\right) + a_3\right) \tag{1}$$

With $a_1+a_2+a_3 = 1$. A similar equation can be written for the reactive part of the load or with a frequency dependency.

In the sequel only the voltage dependency will be considered though.

Another usual model is the exponential load model:

$$P = P_0 \left(\frac{V}{V_0}\right)^{\alpha} \tag{2}$$

The ZIP load model could appear appealing thanks to its physical meaning. However, it is worth to be noted that this model is often used in a measurement-based approach. In this case, the second order model is simply used to fit at best a set of measurements. It is common to obtain (large) negative values for one or two of the a_i parameters [6], without physical meaning.

The exponential load model presents the advantage of having only one parameter (α) instead of two in the ZIP load model. This is an advantage for the identification procedure.

On the other hand, the dynamic load model presents a time dependency that generally describes a recovery of the load: following a voltage variation, the loads reacts instantaneously before recovering towards a power closer to the previous load consumption. This class of model can describe phenomena as different as fast recovery of a motor or slow recovery of a thermostatic controlled load. Another classification is thus required and is addressed in the next section.

The presentation of dynamic load models is limited here to two widely used models.

The first one is the composite motor load model. It is made of two parts: a ZIP load model – which represents the static part of the load – and an induction motor model – which represents the dynamic part of the load [7]–[11]. The induction motor may be represented with different level of complexity. The third-order model is well accepted in power system stability and is used here. The complete equations are given in [8]. This model has 15 parameters to identify.

Another model has been proposed by Hill and Karlsson [12], [13], initially to represent the thermostatic and Load Tap Changer (LTC) recovery of the load which occurs with long time constants in distribution feeders. It is also referred as the Generic NonLinear Dynamic (GNLD) model and is described by the following equations:

$$T_p \dot{P}_r + P_r = N(V) \tag{3}$$

$$P_d = P_r + P_i(V) \tag{4}$$

With:

$$N(V) = P_s(V) - P_i(V) \tag{5}$$

$$P_i(V) = P_0 \left(\frac{V}{V_0}\right)^{\alpha_i} \tag{6}$$

$$P_s(V) = P_0 \left(\frac{V}{V_0}\right)^{\alpha_s} \tag{7}$$

P_d is the final load consumption. The steady state P_s and instantaneous P_i load behavior are voltage dependent with an exponent respectively α_s and α_i. T_p is the recovery time constant and P_0 is the steady state load consumption when the voltage V is equal to nominal voltage V_0. Same type of equations can be written for the reactive part of the load. To distinguish the parameters of the two part of the load, a P or Q subscript is added in the remainder of the paper.

A major advantage of this last model is its reduced number of parameters. The identification procedure is thus largely simplified: 3 parameters (α_s, α_i and T_p) need to be identified instead of 15 in the composite load model.

The Hill and Karlsson model has a major drawback too: the complete decoupling of the active and reactive parts of the load. That makes the models intrinsically incapable to represent a phenomenon like a motor stalling. Transient voltage instabilities need the representation of dynamic motor model [7], [14], [15].

To simulate the evolution of a power system facing large voltage or frequency variations, the choice of static or dynamic load models can cause large differences in the conclusions drawn [5]. A dynamic load model is recommended in this case. However, the adequacy of this model when the system experience condition far to nominal should also be analyzed (see section II-E).

C. Linear vs. nonlinear

For the dynamic models, two types of nonlinearities must be distinguished [16]:

- The nonlinearities in the state variables;
- The nonlinearities in the input variables.

For instance, the Hill and Karlsson load model is linear in its state variable P_r but nonlinear in the input variable V. On the contrary, the composite dynamic load model is nonlinear in the state variables when the complete third order motor equations are taken into account.

Recent work on load identification does not use much linearization in the input variables and generally use nonlinear optimization algorithm. The possibility to linearized in the input variables still remains an interesting option if problems are encountered in the identification procedure.

D. Short-term vs. Long-term dynamics

The loads include dynamic phenomena with time constant ranging from some hundreds of ms to some hundreds of seconds. At the lower end, the dynamic is caused mainly by the active power recovery of the motors driving a mechanical load, which usually takes place in less than 1s. At the higher end, dynamic recovery is observable in presence of resistive heating loads with a thermostatic control. The thermostat will tend to supply the load during longer time interval when a voltage decrease is observed. The aggregated response of a huge group of this kind of loads is seen at the transmission level as something close to a first order recovery. Static load supplied by feeder with LTC can also be seen as dynamic with long time constant from the primary side of the transformer.

A natural link can be made with the two models presented in the previous section. It seems obvious to represent fast dynamic with the composite induction load model and slow dynamic with the Hill and Karlsson model. However, all the models can be used to describe the different dynamic phenomena by a proper fitting of the parameters, mainly the time constant.

E. Small signal vs. large signal models

The behavior of the load faced to small voltage variations (less than 10%, close to nominal voltage) differs from its reaction to more severe voltage drops. For instance, during a voltage dip caused by a short circuit, some loads can be completely disconnected by an undervoltage relay (the main goal of this kind of relays is generally to avoid stalling of induction motor during voltage drop). As a consequence, the load can be reduced drastically after the clearing of the fault.

The models presented above are not able to deal with these large discontinuities but only with small voltage variations [4], [5], [17]. This is especially true for the Hill and Karlsson model which does not capture possible motor stalling.

Field data are required to evaluate the shedding quantity in relation with the importance of the voltage dip (voltage level and duration). That can be made only with long term field data acquisition because tests implying large voltage variations are generally not desirable [4], [18].

F. Load model error

To reduce the errors in the assessment of the load model parameters, it is important to have a better understanding of the origin of the error.

The error of a given model comes from two sources [9], [19]:

- The bias error which is related to the structure of the model relative to the real structure of the load. It can be decreased by an appropriate model choice but cannot be cancelled because no model can fit perfectly an aggregated load.
- The model variance error which is caused by the fact that the data used for identification are noisy. In the case of load model identification, the stochastic changes in the load are the main cause of model variance error. It can be approximated by $\sigma^2 n_p/N$ where σ^2 is the variance of the noise, n_p is the number of parameters of the model and N is the number of training data.

The Hill and Karlsson model is a good model from the model variance error point of view because it has only 3 parameters. However, the bias error is probably higher than for other load model due to its simplicity.

One can also conclude that a load model built on one or two field tests is highly unreliable. A large number of data, recorded on a long period of time is required to constitute a valid load model. This is the only way to decrease the risk that stochastic load variations interfere in the parameters of the model. The procedure detailed in section IV attach a special importance to this point.

G. Conclusion on load models

Clearly, the perfect load model able to deal with all phenomena does not exist. A choice must be made in accordance with the future use of the load model.

This paper focuses on the Hill and Karlsson model. In reference to the categories cited here above, it can be qualified as a dynamic nonlinear measurement-based model, with the main aim of studying long-term dynamic of the load caused by small voltage variations. The section IV details the original methodology developed to identify the parameters of the model. First, a review of the existing identification approaches is presented in the next section.

III. Load model parameter assessment

In this section, different approaches to assess the parameters of a measurement-based model are reviewed. They are presented in three groups in accordance with the type of event that is used. A summary of parameter identification techniques is then presented.

A. Voluntary small voltage variations

The most widely used method to assess the parameters of a load model is to apply a voluntary voltage variation to a load and to record its active and reactive power response. These variations can be caused by different means:

1) *Capacitor bank switching:* the size of the step can be approximated by Q_{cN}/S_{cc} where Q_{cN} is the nominal power of the capacitor bank and S_{cc} is the short-circuit power. In highly developed and meshed network, the capacitor banks are generally not sufficient to generate voltage step of sufficient amplitude.
2) *Switching on/off transformer in parallel with different ratios:* if the load is supplied by two transformers in parallel, they can be put on different ratios. Switching one of them on (if initially only one supplies the load) or off (if initially they both supply the load) can provoke a step of up to 10% [20].
3) *Successive steps of LTC transformer:* the control of the LTC is switched in manual mode and several steps in the same direction are performed. The limits on the variation depend of the minimum or maximum voltage accepted. 5% is common [21], some utilities goes until 8% [20], [22] or 10% [13]. This method is simpler than the second one but the voltage variation is closer to a ramp than to a step. Reference [20] concludes however that the voltage variation method (ramp or step) does not influence the assessment of the parameters.

B. Natural voltage variation of small amplitude

The approaches mentioned in the previous section imply voluntary voltage disturbances of amplitude that can become problematic. In a distribution system, a voltage step of 5 to 10% can already cause a violation of the minimum voltage at the end of the feeder. For an industrial load with sensitive processes, the step in itself can induce some difficulties.

Anyway, these deliberate disturbances required special authorizations and work for the implementation of the measurement devices and for the performing of the tests. This is globally a highly time consuming process. Several experiences with an automated procedure have been made. The idea is to exploit natural voltage change to assess the parameters of a load model.

Reference [23] shows results of a long-term experiment (3 years) where natural disturbances (mainly between 1 and

4%) have been used to assess the parameters of a static exponential load model. The results coming from each event are then statistically studied. Histograms show the number of occurrences of each numeric result. Similar presentation of the results is made in [22]. The pattern of the histograms is close to a Gauss curve. The maximum can thus be taken as a representative parameter with a certain level of confidence.

References [24], [25] use the events detected to assess the parameters of a dynamic load model with short-term time constant. A statistical study is made in [25] where the events are grouped depending on the instant when they appear: day, night or evening and week-end.

Reference [26] is the only one to propose an automated approach to assess the parameters of the Hill and Karlsson model. This kind of model requires maintained disturbance because of the long time constant that must be assessed. The maintained disturbances can be caused only by LTC transformer changes or capacitor switching and are always of small amplitude (less than 2%). Moreover, the identification window must be long enough to assess correctly the time constant (at least around 3 times the time constant). During this window, stochastic variations of the load are likely to be in the same order of magnitude than the natural response of the load to the small voltage step. If the identification procedure succeeds to estimate the parameters of the load model, they will certainly be unreliable because highly disturbed by the stochastic change in the load. For instance, in [26], the results for the steady-state parameters α_s and T_p presents large standard deviations.

Section IV deals with this aspect and proposes another way to assess the parameters of a Hill and Karlsson model when large stochastic variations are observed.

Another important point for these automated procedures is the reliability of the voltage change detection. References [10], [23], [24], [26] use very simple thresholds on voltage changes, possibly with a condition on holding the new value. The proposed method (section IV) goes further and includes an algorithm coming from the fault detection in the control area. This algorithm is able to detect with certainty all the events without giving false alarms.

C. Natural voltage variation of large amplitude

References [8], [9], [27] use voltage variations caused by short-circuits appearing naturally in the power systems. These short voltage steps that are not maintained (the voltage comes back close to its pre-fault value after a short delay) are only suitable for models with a short-term time constant like the composite load model. Static model parameters can also be estimated [27], with the limitation that only the instantaneous reaction is captured if the model is dynamic. In [8], an event that implies a phase to earth fault is used. The positive sequence of the voltage, active and reactive power is then used to fit the parameters of the model. This approach can be discussed; nothing proves that the loads behave in the same way for symmetrical or unsymmetrical disturbances.

The parameters of the linearized composite load model are assessed in [9]. The interesting aspect lies in the identification procedure. Instead of running an identification procedure for each individual event and then computing some statistics, the identification procedure is run on the whole set of data to find the best parameters for all the events together.

D. Parameter identification methods

Once the data are acquired, the identification procedure can be run. This procedure is generally an optimization method because there are more equations than unknowns. If the model is static or linear, the process is quite straightforward and implies linear least square minimization. Two approaches can be considered if the model is dynamic and nonlinear:

- Linearize the model and then run a standard linear optimization method [21], [28];
- Keep the nonlinear model and fit the parameters with a nonlinear optimization method [19].

References [26], [29] compare both approaches without pointing significant differences. Even if the nonlinear approach is more complex, it is widely used, probably due to the availability of the optimization toolbox dealing with nonlinear method in Matlab. The computing ability of current PC is also largely sufficient to use directly nonlinear model without linearization.

The nonlinear optimization methods can be classified in two categories:

- *First order methods:* starting from an initial guess, a gradient information is used to evolve towards a better solution. Newton-Raphson method enters in this category. A major drawback is the risk to fall in a local minimum. The global minimum will be reached only if the starting point is close to it.
- *Zero order methods:* no gradient information is used. Stochastic change or geometric transformations are applied to a set of initial guesses. Simplex method [30], simulated annealing [29], ant colony [10], genetic algorithm [31] methods have been successfully applied to nonlinear dynamic load parameters assessment.

Zero-order methods are generally advised when no other knowledge on the landscape of the function is available. The method presented in the next section is based on the simplex method which presents the advantage to be deterministic. The method is thus easier to understand and one can follow its development. That gives generally a higher acceptance compared to stochastic method, even if they can possibly perform better or faster.

IV. Description of the method

This section describes an original method to assess the parameters of a long-term dynamic load model using natural voltage variations happening at the load bus. As explained in section III-B, this constitutes a real challenge because stochastic load variations can be of the same order (or even bigger) than the natural response of the load to small voltage variations. The procedure uses data of several events averaged together to solve the problem. A set of individual events where the noise (i.e. the stochastic variations) is bigger than the signal (i.e. the natural reaction of the load to the voltage change) can become usable when used together. This is clearly illustrated in the section V.

The initial assumption to develop the method is that continuous recorders are installed at the load bus. They give the rms value of the voltage, the active and reactive power. The refreshment rate must not be very high because the aim is to capture long-term evolution of the load. A value between 1 and 5Hz is sufficient. The measurements can be treated locally or send to a central data gathering system which collect data from several monitored loads.

The continuous records can be used offline, for instance by downloading every month the new data and running on them the procedure described below. Parameters representative of this month of measurements are then obtained. If significant changes are observed with respect to the previous data, parameters can be updated in the simulation models of the power system.

An alternative is to use the records online. Each time that a new event is detected, it is added to the database and old measurements are removed (either one by one or with a forgetting factor decreasing progressively the importance of old measurements in the database). The identification process gives a new value of the parameters after each event. This online approach can be interesting if a link is made with the security assessment software to update regularly the load model parameters.

An offline method with a monthly refreshment rate would already represent a huge improvement compared to the one-shot method described in the section III-A. The procedure is presented in this way below. It is composed of three main parts: the event detection, the averaging process and the identification algorithm.

A. Event detection

The aim is to detect efficiently steps or fast variations in the voltage. Compared to simple trigger, the method is very robust with respect to noise and do not detect voltage dips lasting for a short interval of time.

The method is based on a Cusum (CUmulative SUM) algorithm [32], which originates from the fault detection field in a control context. It is generally used to detect faulty sensors and is very robust to noise.

In its original version the Cusum algorithm follows these steps to detect fault in a vector of measurements z:

1) Compute an initial mean μ_0 of the vector z, initialize cumulative sum g_0 to zero and choose two thresholds: β and h.
2) For each new sample z_i, compute $g_i = max(0, g_{i-1} + z_i - \mu_0 - \beta/2)$. If $g_i > 0$, increase the variable delay d by one. Else, put d to 0.
3) If $g_i > h$, a fault is detected. The time of the fault is given by $i - d$.

Therefore, the algorithm detects an increase of the value of z larger than $\beta/2$ after a certain delay depending of the value of h. This delay is precisely what gives the noise immunity

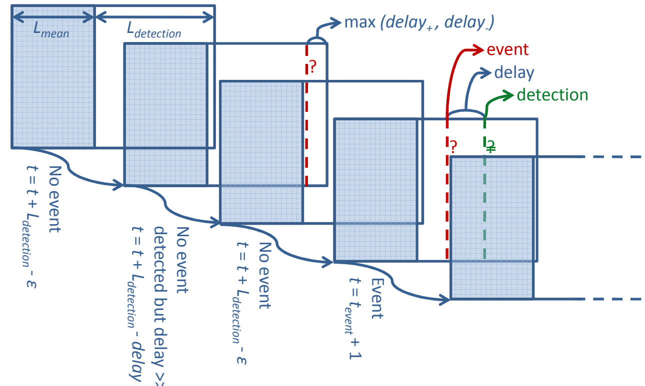

Fig. 1. Succession of windows for the modified cusum algorithm

to the algorithm. The application to the detection of variation in the voltage needs some adjustments:

- Variation in both directions (increase or decrease of the voltage) must be detected. The cumulative sum g is replaced by two variables g_+ and g_-. This is common and is referred in the literature as a two-sided Cusum algorithm.
- The voltage may evolve slowly due for instance to normal load evolution along the day. With an algorithm running continuously, these slow evolutions would be detected (after a long delay). To avoid this, the algorithm has been modified in a windowed version (figure 1). The process is essentially the same but μ_0 is recomputed regularly (colored window). The cumulative sum is run only on a limited subsequent window (blank rectangle). If no event is detected, both windows are then slided towards the new samples. When an event is detected, a new window begins just after it.
- Finally, to facilitate the use of the algorithm, the input parameters β and h have been replaced by more meaningful parameters: the minimum variation percentage and the maximum time to reach this variation (for instance: detect change of 1% occuring in less than 20s).

The threshold should be chosen to detect the LTC transformer (usually around 1%). Voltage dips are not detected thanks to the delay of the Cusum algorithm. All events detected qualify for a long-term load model assessment from the point of view of the voltage variation.

B. Averaging process

All the events detected by the Cusum algorithm are averaged together to obtain data with a very high signal to noise ratio. The process includes the following steps:

1) Only events implying voltage step of the same amplitude must be used. Indeed, the model is nonlinear and the average of the inputs (V) does not give the average of the outputs (P and Q). Fortunately, because the events are due to tap changes, they are all of the same size. The only events to remove are those with several steps in the windows that will be used for the identification procedure.

2) All events are normalized with their mean pretrigger value (V, P and Q). In the equations 6 and 7, V_0, P_0 and Q_0 become equal to 1. It can be shown mathematically that the approximation made is very small.
3) A step direction is chosen. All the events in the other direction are reversed to be in the chosen direction.
4) Voltage, active power and reactive power of all events are averaged.

With a sufficient number of events, the stochastic variations of the load are largely reduced and the parameters of the model can easily be estimated if the model structure is good.

C. Identification algorithm

The averaged signals are used to run a nonlinear optimization algorithm that gives the value of the Hill and Karlsson model parameters. The simplex method is used. The optimization of a problem with n variables includes the following steps:

1) Starting from an initial solution, an initial simplex is constructed. A simplex is a geometric form with at least $n+1$ vertexes in the n-dimensional parameters space.
2) A cost value is associated at each vertex. Here, the cost function is a standard square error function between the measurements and the model assessed with the parameters of the current vertex.
3) Geometric transformation is applied to the point with the highest cost. The transformation applied includes reflection, extension and contraction with respect to the barycentre of the other vertexes.
4) The procedure is continued until the convergence of the vertexes.

Several simplex algorithm have been tested, namely those of [30], [33] and some variants of them. The procedure to construct the initial simplex has also been changed, as well as the number of vertexes includes in the simplex. Finally, it is difficult to decide between the methods because each variant can give the better results in some cases. The simplex method described in [30] (available in the Matlab optimization toolbox: *fminsearch* function) can be used with confidence.

An interesting option can however be implemented. In reality, physical bounds are known for the parameters of the model by engineering judgment. If a parameters θ has a known limited interval $[\theta_m \theta_M]$, it can be replaced by another variable ζ which will be without bounds. Two transformations can be used: inverse tangent and hyperbolic tangent [33]. The latter is:

$$\zeta = arctanh\left(\frac{2\theta - (\theta_M + \theta_m)}{\theta_M - \theta_m}\right) \qquad (8)$$

The identification process with this reduction of the search space is less time consuming. The transformation can also help the convergence. In some case, the simplex with the set of initial parameters fails to converge while the one with the modified set succeeds.

V. Results

Two measurement campaigns have been run in the Belgian power system. The results of the first one are detailed here.

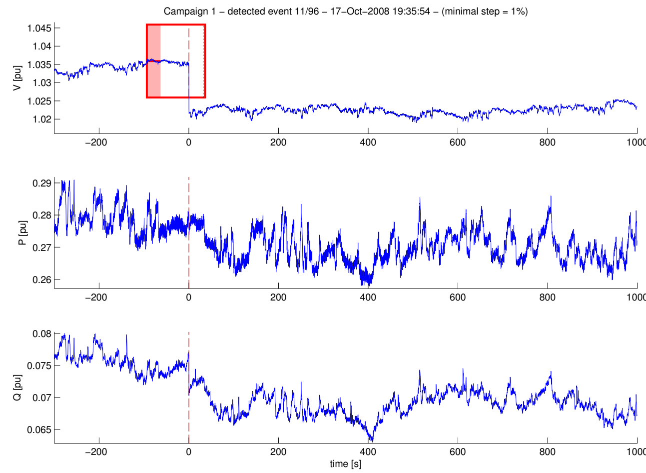

Fig. 2. Event detected on the voltage. The colored rectangle shows the window to compute the initial mean μ_0, which is represented by the tick horizontal segment. The event occurring at the time indicated by the dashed line is detected at the time shown by the dotted line.

The measurements have been taken continuously during 13 days on a distribution load supplied by a 150/11kV transformer with a LTC (steps of 1.8%).

Due to the short length of the feeders, they are not equipped with voltage regulators or automatically-switched capacitors. As a result, the feeder load responds to voltage disturbances with its natural characteristic. The short-circuit power is large enough to limit disturbance in the voltage caused by capacitor switching in transmission system or load change to very small amplitude. Hence, these events are not detected by the Cusum algorithm.

The load evolves between 17 and 30MW with a power factor around 0.97 (nominal power of the transformer is 50MVA). No complementary information on the mix or on the composition of the load is available.

The Cusum algorithm detected 96 events during the 13 days. All steps due to LTC are observed and no other cause leads to detection. Figure 2 shows one event on the voltage, with the corresponding active and reactive power. As can been seen, the stochastic variation are huge. The simplex algorithm is unable to converge on this kind of event and, even if it succeeds, the parameters would be unreliable.

All the events are then grouped together with the averaging process. Six events are excluded by the filter because several steps in the same direction appeared in the identification window. Ninety events remain. Their average can be seen on figure 3. The signal to noise ratio is much better and the natural response of the load to the voltage change is clearly visible. A bigger number of events would have been preferable on this highly disturbed load.

The active power behaves essentially as a static load. This result was expected because the part of electric heating is small in the Belgian load and the short feeders are not equipped with LTC. The reactive power presents a slight recovery with a time constant of 60s. The second campaign conducted on a different load shows very similar results: the active power is static and the reactive power is dynamic with a more visible recovery.

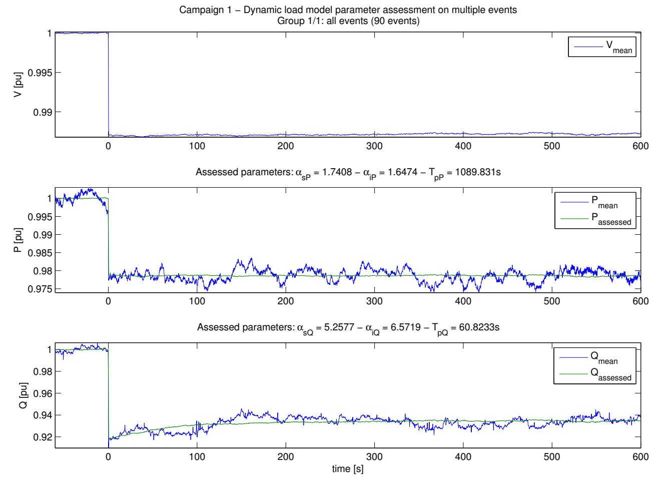

Fig. 3. Results of the dynamic load parameter assessment on an average of 90 events.

The identification process gives the following results:

- Active power: $\alpha_{sP} = 1.7408$, $\alpha_{iP} = 1.6474$, $T_P = 1089.8s$. The slight difference between the two voltage exponents shows that the load is static. In this condition, the time constant is not reliable and is more linked to the remaining stochastic variation. As the time constant is bigger than the size of the windows, the static behavior of the load is here better represented by the α_{iP} exponent.
- Reactive power: $\alpha_{sQ} = 5.2577$, $\alpha_{iQ} = 6.5719$, $T_Q = 60.823s$. The exponents here are clearly different; the time constant is thus well estimated. The high value of the exponent can be explained by the conjunction of two elements: the magnetic components operating in saturation zone [2] and the reactive compensation of the load in distribution network [34].

VI. Conclusion

Inaccuracy in the parameters of the load model or inadequate model can cause important mistakes in power system simulations, especially in the area of dynamic simulations.

This paper presents an original method to identify the parameters of a *dynamic* load model in an automated way. The measurements given by a continuous recorder are analyzed by a robust algorithm to detect voltage steps caused by the LTC moves. The high random variation of the load with respect to the small variation caused by one step of the LTC makes the identification procedure of individual event impossible and/or unreliable. An averaging process is run, using all the events detected during a long measurement campaign. An identification procedure is then run to find the parameters of a Hill and Karlsson model that described the load at best.

Results of a measurement campaign in the Belgian power system are presented. A second campaign has been made, leading to similar results. The active load behaves predominantly as a static load. The reactive load presents a slight recovery with a time constant around 60s.

Industry is asking for low-cost dynamic load monitoring device [35]. The presented method can be seen as a step into this direction, proposing a method that can be used for the software of such device.

Several perspectives of this work can be cited. Longer campaigns could allow analyzing the variability of the parameters of the loads along the day, the week and the year. A large measurement campaign can also be conducted to study the discrepancies between several load busses of the power system. The Belgian transmission system operator launched a large campaign that will record the evolution of the loads from the dispatching. A first analyzis of the measurements shows that their sensitivity is sufficient to study the load model, at least statically. The main advantage is that the campaign is very easy and cheap to implement.

Other load models can also be estimated with a similar approach. The Hill and Karlsson model has been chosen here because it fits the measurements well. A real complete automated procedure should ideally include an algorithm to select the appropriate load model structure before identifying the parameters.

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