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Measurement-based Load Modeling using Transfer Functions for Dynamic Simulations

Igor F. Visconti, D. A. Lima, J. M. C. S. Costa, N. R. B. C. Sobrinho

***Abstract* - Measurement-based load modeling is a promising approach to reliably represent load behavior in dynamic simulations of large power systems. This paper presents a methodology that starts with the acquisition of voltages and currents from power quality monitoring systems and highlights the issues associated with selecting, processing and resampling the data to estimate the relationship between the power deviations as a function of the voltage deviations. The load model mathematical structure chosen is a second-order transfer function, whose parameters are estimated using a genetic algorithm (GA) as the optimization technique that minimizes the error between the real data that are measured and the data that are simulated with the proposed models. Some insights were achieved regarding the appropriate search space choice.**

***Index Terms*— Load modeling, Power system monitoring, Artificial intelligence, Genetic algorithms, Power quality, Power system transient stability, Systems identification, Voltage dips.**

NOTATION

Constants

V_0	Pre-fault voltage recorded at the analyzed bus.
P_0	Pre-fault active power recorded at the analyzed bus.
Q_0	Pre-fault reactive power recorded at analyzed bus.
n_s	Integer that represents the total samples from a recorded power curve.
N	Integer that represents the total number of selected contingencies.
ev	Integer variable that indices the recorded contingencies.
Δt	Sampling period set in the monitoring device (in this work, 0.000521 sec).

Parameters

$\omega_{1p}, \omega_{2p}, \omega_{0vp}, \omega_{1vp}, \omega_{2vp}$	Parameters to be estimated for the active power load model.
$\omega_{1q}, \omega_{2q}, \omega_{0vq}, \omega_{1vq}, \omega_{2vq}$	Parameters to be estimated for the reactive power load model.
$\alpha_{0vp}, \alpha_{1vp}, \alpha_{2vp}, \alpha_{1p}, \alpha_{2p}$	Active power parameters set for the *s*-domain transfer function.
$\alpha_{0vq}, \alpha_{1vq}, \alpha_{2vq}, \alpha_{1q}, \alpha_{2q}$	Reactive power parameters set for the *s*-domain transfer function.

Variables

m	Integer that indicates the number of past samples that are taken into account to evaluate the actual power.
t	Integer variable that indices data sampled at equal discrete intervals.
$V(t)$	Voltage recorded at instant t.
$P(t)$	Active power evaluated when $V(t)$ deviates significantly from V_0.
$Q(t)$	Reactive power evaluated when $V(t)$ deviates significantly from V_0.
$P(s)$	Active power evaluated for the *s*-domain.
$Q(s)$	Reactive power evaluated for the *s*-domain.
$P(z)$	Active power evaluated for the *z*-domain.
$Q(z)$	Reactive power evaluated for the *z*-domain.
$F(\theta_p)$	Real value that evaluates the quality of a parameter for active power load models.
$F(\theta_q)$	Real value that evaluates the quality of a parameter set for reactive power load models.
$P_m(ev,t)$	Active power measured for a given contingency (*ev*) and a given time *t*.
$Q_m(ev,t)$	Reactive power measured for a given contingency (*ev*) and a given time *t*.

Sets

$\theta_p(s)$	Set of parameters to estimate the active power in the *s*-domain.
$\theta_q(s)$	Set of parameters to estimate the reactive power in the *s*-domain.
$\theta_p(z)$	Set of parameters to estimate the active power in the *z*-domain.
$\theta_q(z)$	Set of parameters to estimate the reactive power in the *z*-domain.

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I. Introduction

One of the main objectives of an electric power system is to support load variations with reliability, maintaining synchronism among all generation units and damping oscillations after small and/or large perturbations that routinely occur. For this reason, operation and planning engineers rely on dynamic simulations to help decisions on control actions to manage normal operations and to fulfill operational and economic constrains. Nevertheless, to represent a power system's behavior accurately, it is essential to have models of all the elements that compose an electric power system under study that are as accurate as possible. Among all these elements, the equivalent load representation is the most difficult task to accomplish.

The load modeling challenge is to find an equivalent to the aggregation of the many electric and electronic devices supplied by a power system bus bar (usually known as load bus bar). The amount of devices switched on and switched off varies not only during the day but also during the week and through different seasons, which means that it may not be possible to represent all the scenarios using a single equivalent model. The most typical approach relies on representing a specific load bus bar by three different classes, such as low, medium and heavy loads.

It is well known that load modeling is a key factor in power system simulations [1]-[4]; for instance, if the power deviation evaluated by a load model implemented in a simulation is too small, the power system stability margins may be underestimated and can lead to a voltage collapse. However, if the power evaluated by an implemented load model is too great, full advantage is not taken of the transmission line resources [5].

In general, all around the world, power systems operate closer to their transfer limits, which represents a reliability risk and the precise evaluation of the stability margins and transfer limits will be an essential task; load modeling has an important role in building power system representations.

Transmission companies seldom have information about the distribution systems connected to them. However, when these companies need to perform dynamic studies, simulating contingencies to evaluate the system performance, these distribution systems must be represented by an equivalent that will behave as if the load mix was represented by a single component.

This article is motivated by the influence of the load behavior on voltage stability and rotor stability studies. Additionally, this work presents results from an R&D project that aims to model up to 50 distribution systems connected to the transmission system through 230/69 kV delta-wye transformers. This transmission utility wants more accurate dynamic simulations and needs better equivalent models from several distribution systems spreading through the northern Brazilian grid. Some of these systems can contain Distributed Generation (DG). Although not all 69kV systems are radial, this modeling procedure is aimed for radial systems downwards to the measuring point, which is the low-side of the 230/69kV transformers. Whenever there is more than one transformer operating in parallel, it is assumed the energy supplied is equally divided between them, since they usually have the same impedances and the same power rating.

Based on these factors, the main contributions of the paper are:

- A procedure to model load dynamic equivalents, using historical data and a genetic algorithm (GA) to estimate the parameters of the load model.
- To discuss and present a real case study to validate the proposed method for general and/or specific contingencies.

The article is divided as follows: section II describes the proposed methodology, section III presents the load model mathematical structure chosen for this work, section IV presents the results of a parameter estimation for both generic and specific load modeling, section V shows the results of the estimated model implemented in a dynamic simulation using the Brazilian national integrated power system and comparing the results with a static ZIP load representation still used for electromechanical studies, and finally, Section VI presents conclusions and future developments.

II. Proposed Load Modeling Methodology

Load modeling could be described essentially as a system identification task [6] based on a measurement-based approach as presented in [7]-[9]. One way to perform load modeling is to adopt a heuristic process, summarized as follows:

i. Selecting feasible input/output data and clustering the data into training and validating subsets;
ii. Choosing a suitable mathematical model for the load representation;
iii. Adjust the model parameters to best match the simulated output with the measured data;
iv. Validate the load model by means of specific criteria.

Because the main goal is to develop a better load representation that describes both active and reactive power as functions of voltage deviations, selecting feasible input/output data means establishing a database with records of the active power, reactive power and voltage before, during and after disturbances that are more likely to occur in bulk power systems, which could be considered the most typical disturbances.

One may be interested in choosing data from disturbances that occurred upstream, i.e., outside the equivalent system; in this case, it is not desirable to model a system under a contingency because the system's network topology will change by system protection actuation. In this work, only the first cluster will be used. Fig. 1 presents an example of the processed data: a positive sequence active power component (red curve, left axis) and a positive sequence voltage component (green curve, right axis).

Because these load models are intended to be implemented in dynamic simulations for a transmission utility, a positive sequence was chosen, assuming that in transmission, the system loads are balanced. In addition, for the proposed model, one advantage of dealing with positive-sequence signals is the possibility to choose a single input-single output mathematical model.

Therefore, V1 x P1 is input/output data pairs, and Fig. 1 shows graphically an example of one contingency. Of course, for reactive power load modeling, V1 x Q1 is the input/output data pairs.

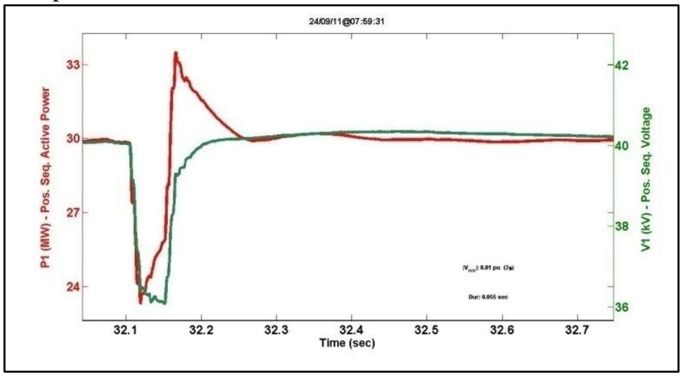

Fig. 1 – An active power positive sequence component (P1) against a voltage positive sequence component (V1), recorded at a 69 kV load bus bar.

All data are stored in a relational database, filtering only the events suitable for load model parameter estimation, where these events are the effect on the input/output data pairs of the disturbance outside the system to be modeled. The next step is to cluster a portion of available data into a training data set and another portion as a validation data set. Fig. 2 summarizes the entire iterative process.

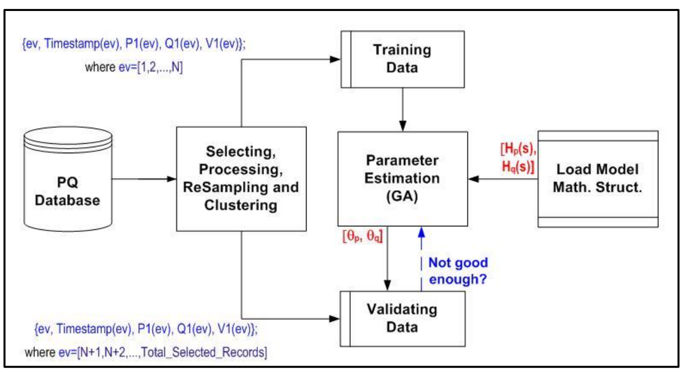

Fig. 2 – Load modeling schematic procedure.

III. Describing the Proposed Model

Considering that the main goal of this work is to develop more accurate load models for dynamic studies, several mathematical structures that relate the power consumed by the load as a function of the voltage dynamics have been studied, and the most commonly used models are presented in [7] and [10].

All of the different load models used in power system simulations can be built by adjusting a parameter set until the model's simulated output data best matches the measured output data. Fitting simulated data to measured data may describe the typical patterns of a load bus, which is, in this context, a point of common coupling between transmission and distribution systems, so the transmission system can "see" a dynamic equivalent of a large mix of the consuming devices. Some of these distribution systems may have a dispersed generation, and their equivalents may behave in a different way.

In this work, engineering insight was the main guide for designing the mathematical structure, formulated as a difference equation [6]. Pre-disturbance operational values are incorporated to the formulation, inspired by the traditional ZIP-load model, resulting in equation (1):

$$\begin{aligned} P(t) &= P_0 \cdot \left[\sum_{m=1}^{2} \omega_{mp} \cdot \frac{P(t-m)}{P_0} + \sum_{m=0}^{2} \omega_{mvp} \cdot \frac{V(t-m)}{V_0}\right] \\ Q(t) &= P_0 \cdot \left[\sum_{m=1}^{2} \omega_{mq} \cdot \frac{P(t-m)}{P_0} + \sum_{m=0}^{2} \omega_{mvq} \cdot \frac{V(t-m)}{V_0}\right] \end{aligned} \tag{1}$$

The second-order model was the mathematical structure that gave best results and, due to this model's flexibility and theoretical acknowledgement available in the literature, was chosen for both the active and reactive power load modeling.

Because a discrete time-domain transfer function can be derived from (1) by using the z-transform [11], the relationship between the transfer function poles and the model's response to disturbance can be investigated. Equation (2) presents this transfer function:

$$\begin{aligned} P(z) &= \frac{P_0}{V_0} \cdot \left[\frac{\omega_{0vp} \cdot z^2 + \omega_{1vp} \cdot z + \omega_{2vp}}{z^2 - w_{1p} \cdot z - w_{2p}}\right] \cdot V(z) \\ Q(z) &= \frac{Q_0}{V_0} \cdot \left[\frac{\omega_{0vq} \cdot z^2 + \omega_{1vq} \cdot z + \omega_{2vq}}{z^2 - w_{1q} \cdot z - w_{2q}}\right] \cdot V(z) \end{aligned} \tag{2}$$

Each parameter set is presented in (3):

$$\begin{aligned} \theta_p(z) &= [\omega_{0vp}, \omega_{1vp}, \omega_{1p}, \omega_{2p}] \\ \theta_q(z) &= [\omega_{0vq}, \omega_{1vq}, \omega_{1q}, \omega_{2q}] \end{aligned} \tag{3}$$

These parameter sets were reduced from 5 to 4 elements each because in (1), $P(t=0) = P_0$ and $Q(t=0) = Q_0$. Therefore, the parameters must sum to one, in each model. Some stability constraints are well known for discrete-time transfer functions; the most important constraint restricts the magnitude of the transfer function poles in (2) to less than one [12]. This stability constraint implies that the load model parameters are bounded, and consequently, the solution search space is much more restricted. Therefore, it was necessary to study the continuous transfer function counterpart because the poles can assume a wider range of values. In section V, both mathematical structures were studied, and their results will clarify and motivate this explanation.

Using the Tustin bilinear transformation, a continuous time-domain transfer function is shown in (4):

$$\begin{aligned} P(s) &= \frac{P_0}{V_0} \cdot \left[\frac{\alpha_{0vp} \cdot s^2 + \alpha_{1vp} \cdot s + \alpha_{2vp}}{s^2 + \alpha_{1p} \cdot s + \alpha_{2p}}\right] \cdot V(s) \\ Q(s) &= \frac{Q_0}{V_0} \cdot \left[\frac{\alpha_{0vq} \cdot s^2 + \alpha_{1vq} \cdot s + \alpha_{2vq}}{s^2 + \alpha_{1q} \cdot s + \alpha_{2q}}\right] \cdot V(s) \end{aligned} \tag{4}$$

The parameter sets for both the active and reactive power load models (5) are now defined as follows:

$$\theta_p(s) = [\alpha_{0vp}, \alpha_{1vp}, \alpha_{1p}, \alpha_{2p}]$$
$$\theta_q(s) = [\alpha_{0vq}, \alpha_{1vq}, \alpha_{1q}, \alpha_{2q}] \qquad (5)$$

These parameter sets were reduced from 5 to 4 elements because when the parameters from (1) sum to unity and (2) are transformed into (4), $\alpha_{2vp} = \alpha_{2p}$ and $\alpha_{2vq} = \alpha_{2q}$. Some stability constraints are well known for continuous transfer functions; the most important constraint determining the real parts of the transfer function poles must be negative [12].

IV. Load Model Parameter Estimation

Estimating transfer function parameters by optimization consists of determining an objective function to be minimized (or maximized), which will guide the solution search algorithm. In this work, the objective function will be formulated to minimize the error between the measured power and the load model's simulated power. The genetic algorithm (GA) was chosen to be the optimization technique because of this algorithm's flexibility of implementation [13].

There are two main approaches for choosing the training data to estimate a parameter set. One may need a parameter set that best describes the power behavior for the typical contingencies that are most likely to occur. In other words, this approach intends to find, within a given parameter's solution search space, a generic load model that is supposed to simulate the power dynamics for a set of selected contingencies recorded by monitoring system. Therefore, the objective function to be minimized by the GA will be formulated as the relative mean squared error between the measured power data and the power data calculated by (1) for all of the selected contingencies. Equation (6) describes the objective functions for active and reactive power:

$$F(\theta_p) = \frac{1}{N} \cdot \sum_{ev=1}^{N} \frac{1}{n_s} \cdot \left[\sum_{t=0}^{n_s-1} \left[\frac{P(ev, t\Delta t) - P_m(ev, t\Delta t)}{P_m(ev, t\Delta t)} \right]^2 \right]$$
$$F(\theta_q) = \frac{1}{N} \cdot \sum_{ev=1}^{N} \frac{1}{n_s} \cdot \left[\sum_{t=0}^{n_s-1} \left[\frac{Q(ev, t\Delta t) - Q_m(ev, t\Delta t)}{Q_m(ev, t\Delta t)} \right]^2 \right] \qquad (6)$$

The other approach is to reproduce one event by using data recorded before, during and after from this specific event of interest, which means, in this case, that *N*=1 for Equation (6) evaluation.

V. Results and analysis

The contingencies recorded are triple, double and single phase voltage sags. Selecting contingencies is a key factor for establishing a representative training data set; voltage sag minimum RMS magnitude, duration of the contingency and contingency type are indicators used to establish typical contingencies.

Finding generic load model means estimate a parameter set as precise as possible to simulate different voltage sags, which means different types of voltage sags (one-, two- or three-phase drops), different severities (minimum voltage during disturbance) and for different scenarios (different pre-disturbance load levels P_0, Q_0, different hour of the day, day of week, etc.). Therefore, the choice of training data set and validation data set for estimating and availing a load equivalent representation is crucial for obtaining a general load model.

However, it is sometimes necessary to better understand a specific contingency in a *post-mortem* analysis. For this case, whenever a record of this specific disturbance is available, it is considered the best way to estimate an equivalent load model to represent that subset of the main system. This section presents results for both approaches.

A. Estimating a parameter set for typical contingencies

To find a parameter set that best simulates different contingencies, one must retrieve from the database some representative ones to act as training data. Their indicators (minimum RMS voltage, duration, type…) must range within an expected value, characterizing a typical behavior of a specific distribution system to be modeled.

Expression (7) presents the formulation of the active power load model estimated for typical contingencies recorded in a 69kV load bus bar, and Fig. 3 presents a selected set of recorded contingencies (red curves) and the results (blue curves) of the proposed model (1), which have been adjusted by an estimated parameter set (3).

Each blue curve is calculated by the equation presented in (7), and each curve is disturbed by its respective recorded voltage sag, whose data sets are not shown in the figure; instead, all graphics show the RMS minimum voltage value per unit at the bottom of each graphic, indicating the disturbance severity. Because the transmission utility studied still uses a generic ZIP load model for dynamic simulations, this generic model was plotted (green curves) in each graphic and subjected to the same voltage sags .These contingencies were caused by disturbances of different types, originated at the transmission level.

If the GA finds a solution that is able to simulate power behavior during and after the selected contingencies, it should be verified if this solution can represent the contingencies that are separated for validating the proposed model. All of the data chosen for the training data set were recorded in 2011, as shown in the timestamps presented above each graphic. For validating this model, it is essential to use a different dataset, recorded at the same site, to validate the estimated model's capacity to generalize, i.e., to represent the behavior of that distribution system for other recorded disturbances.

The contingencies recorded during 2010 are presented in Fig. 4; note that the same parameter set (7) estimated for the training data was able to represent different events accurately during and after disturbances originated at the transmission level.

Fig. 5 presents results from two different parameter estimates performed by the GA. One estimate attempted to find a parameter set $\theta_p(z)$, as formulated in (3), for a discrete transfer function, as formulated in (2), and its error minimization process is represented by the blue curve; the second parameter estimate aimed to find a parameter set $\theta_p(s)$, as formulated in (5), for a continuous transfer function, as formulated in (4), and its error minimization process is represented by the red curve. Fig. 5 shows that both parameter estimates resulted in similar errors. Therefore, for active power parameter estimates, none of the tested heuristics proved to perform better.

$$P(\theta_p, t) = P_0 \cdot [1.889 \cdot \frac{P(t-1)}{P_0} - 0.899 \cdot \frac{P(t-2)}{P_0} + 2.56 \cdot \frac{V(t)}{V_0} - 5.04 \cdot \frac{V(t-1)}{V_0} + 2.484 \cdot \frac{V(t-2)}{V_0}]$$
$$\theta_p = [1.889, -0.899, 2.56, -5.04] \quad (7)$$

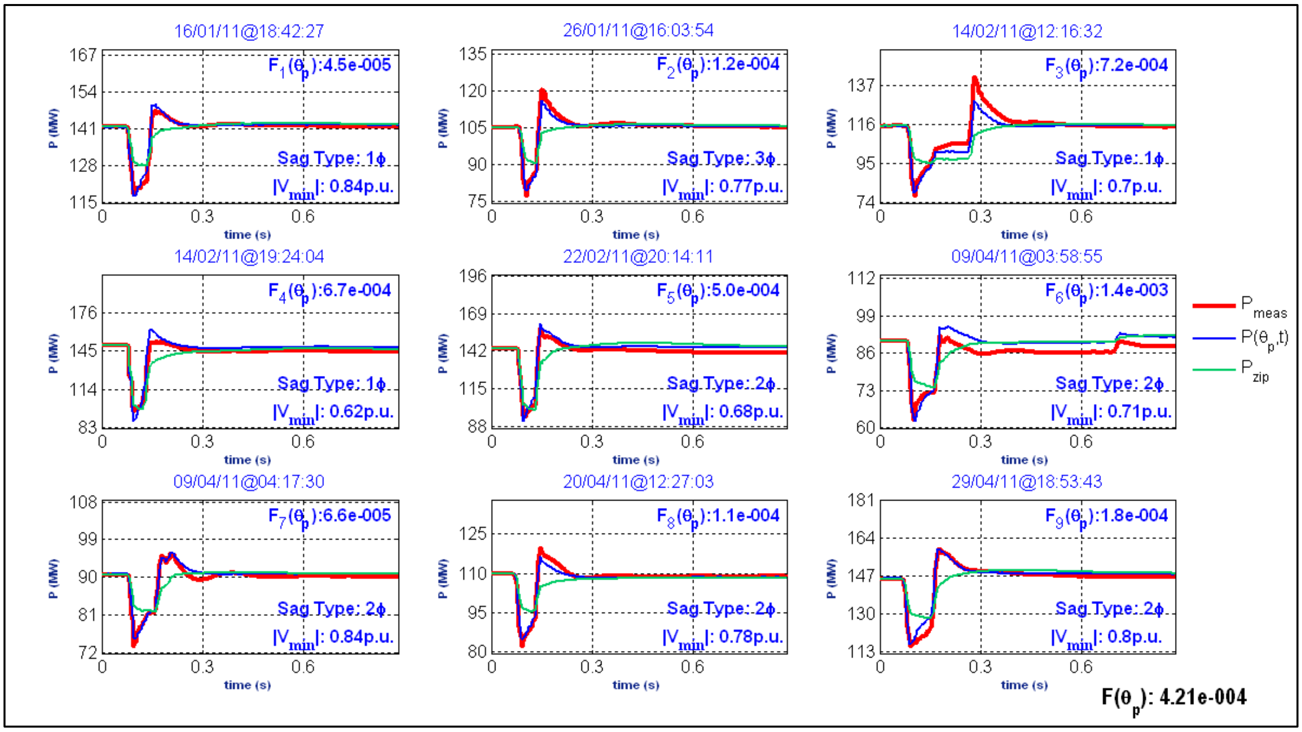

Fig. 3 – Comparison between the measured P (red curve), the P simulated by the estimated model (blue curve) and the P described by a generic ZIP model (green curve).

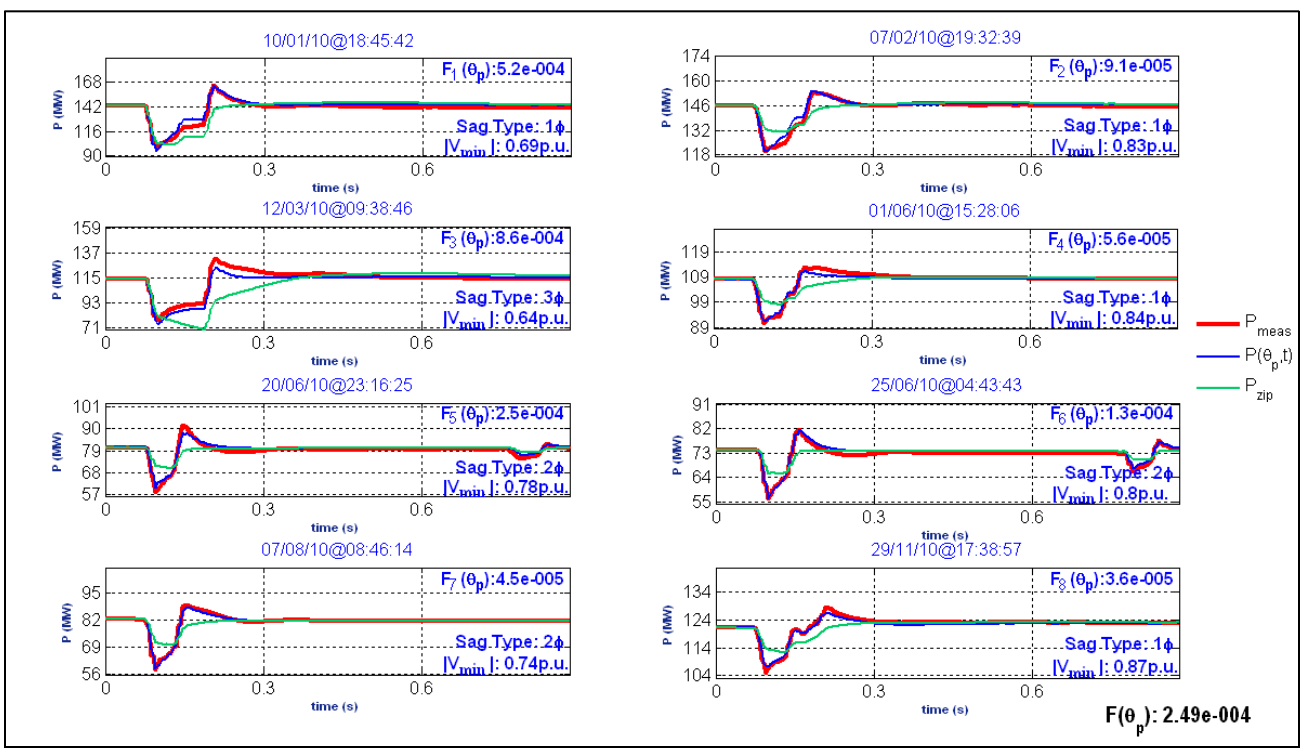

Fig. 4 – Validating the estimated active power model for the 2010 contingencies.

It is more difficult to find a generic load representation for reactive power load modeling because there are devices installed through distribution systems for reactive compensation, such as switched capacitor banks and reactors, and these devices may be or may be not switched on in a given day and may have a completely different configuration in another day.

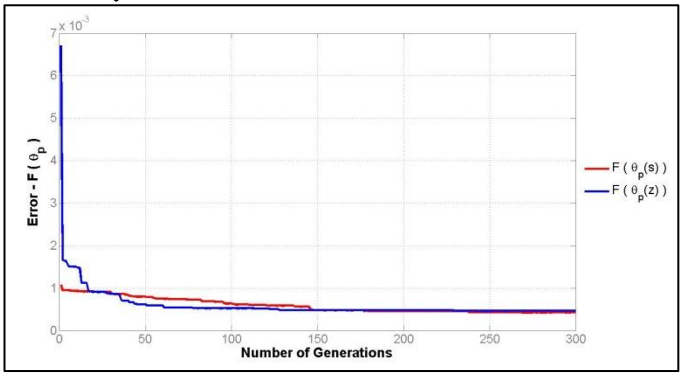

Fig. 5 – Error minimization process for parameter estimate shown in Fig. 3.

Additionally, this network topology for reactive compensation may be quite different over the course of a single day because of different load demand profiles. During the results analysis, it was noted that the reactive-power load model is very sensitive to the steady-state amount of reactive power flowing before a contingency.

Expression (8) presents the formulation to the reactive power load model for typical contingencies, and

Fig. 6 shows that the estimated model could represent records where Q_0~30 Mvar, for both the training data and the validating data, whose results are shown in Fig. 7. For those events where Q_0 was higher than 30 Mvar, the estimated model was more pessimistic, and for "low Q_0", the estimated model was more optimistic. Fig. 8 displays the parameter estimates using a discrete (2) and a continuous (4) second-order transfer function. Note that both functions manage to achieve similar final error results, but searching a parameter set (5) was much faster. This result may suggest that a continuous parameter set search space is better explored by the GA.

$$Q(\theta_q, t) = Q_0 \cdot [0.28 \cdot \frac{Q(t-1)}{Q_0} - 0.63 \cdot \frac{Q(t-2)}{Q_0} + 7 \cdot \frac{V(t)}{V_0} + 1.9 \cdot \frac{V(t-1)}{V_0} - 8.7 \cdot \frac{V(t-2)}{V_0}] \qquad (8)$$
$$\theta_q = [0.28, -0.63, 7, 1.9]$$

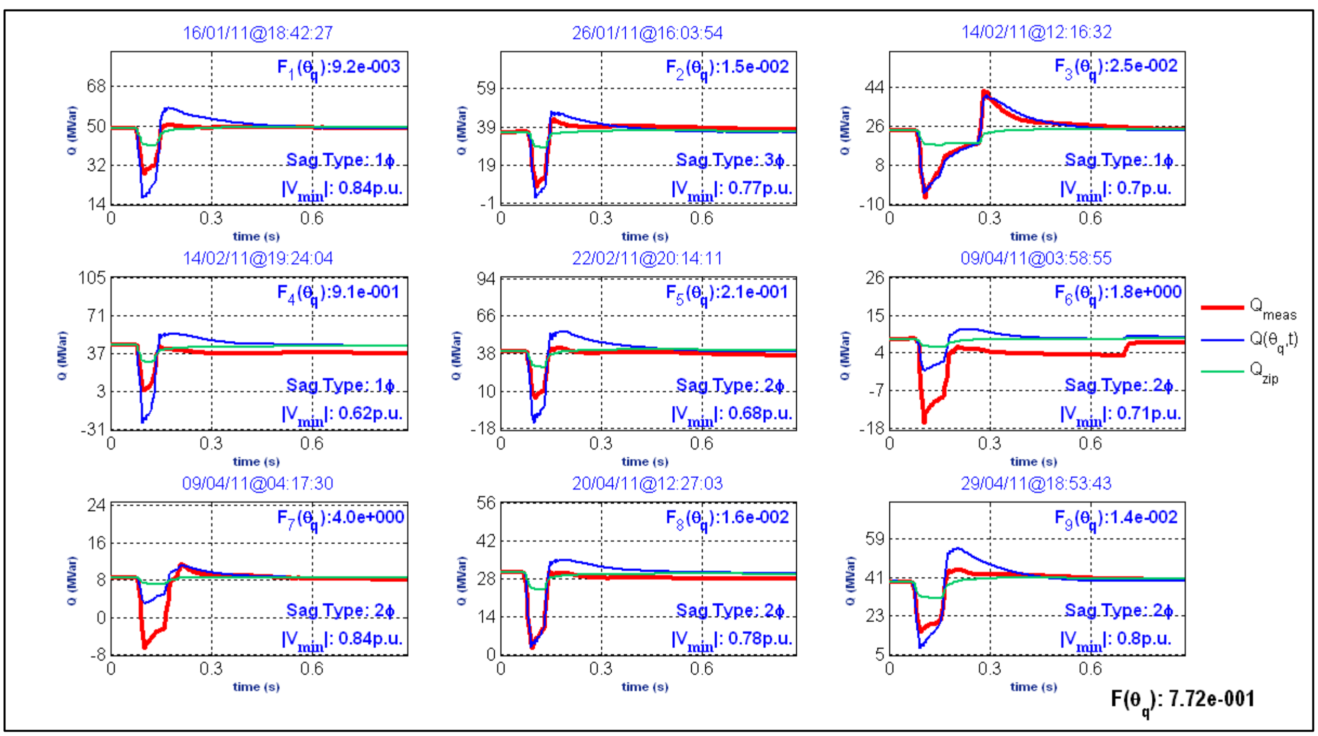

Fig. 6 – Comparison between the measured Q (red curve), the Q simulated by the estimated model (blue curve) and the Q described by a constant-impedance load model (green curve).

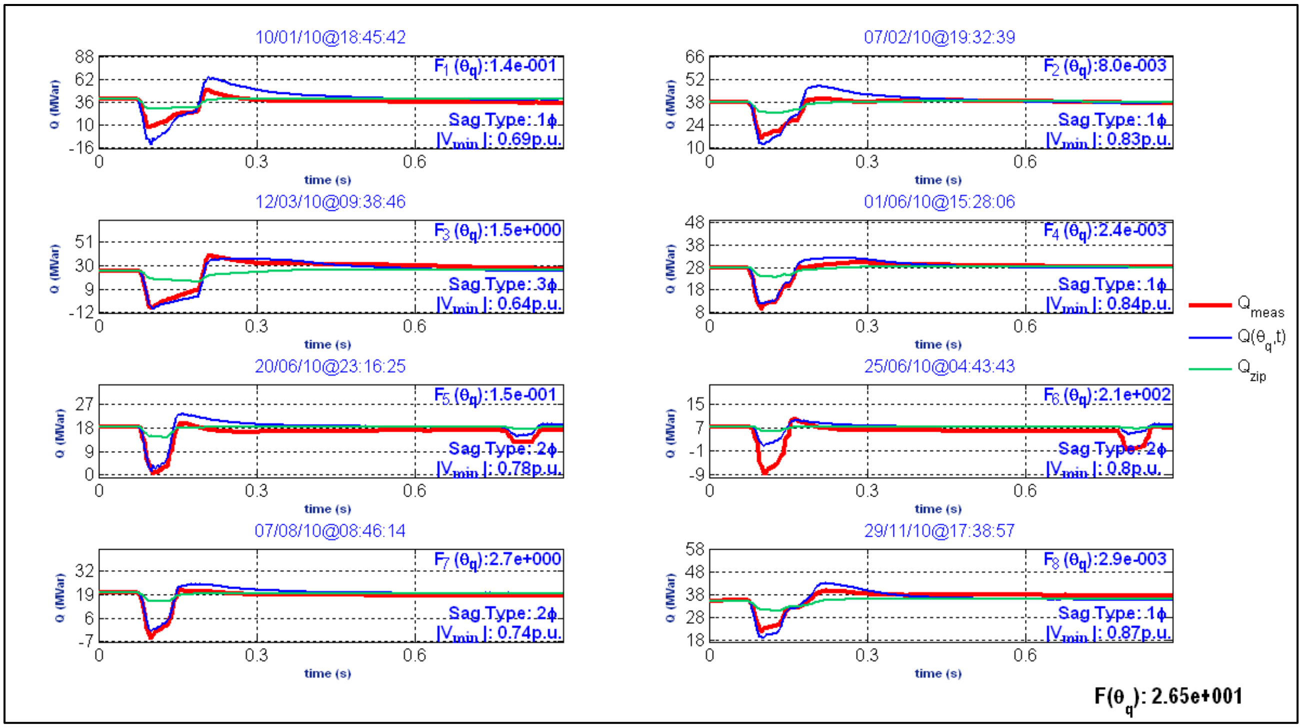

Fig. 7 – Validating estimated reactive-power model for 2010 contingencies.

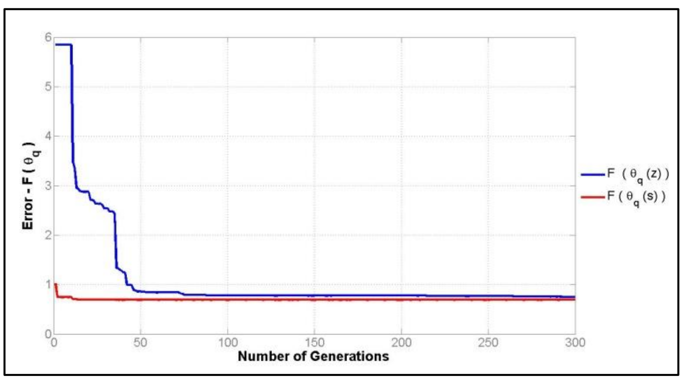

Fig. 8 - Error minimization process for parameter estimation shown in

Fig. 6.

B. *Estimating a parameter set for a specific contingency*

The approach discussed in this section is used when there is no need to find a parameter set that best fits most typical contingencies but rather a set that fits a specific real disturbance. The example above uses data from a disturbance recorded by an Intelligent Electronic Device (IED) at a 69 kV bus bar. According to utility's operational report, this disturbance was caused by an atmospheric discharge on a 230 kV transmission line near the 230/69 kV transformer. The distribution system connected to this line is a 69 kV bus bar, which differs from the other systems presented until now because it contains within its system two thermo-generators with installed capacities of 110 and 30 MW each. Fig. 9 shows a schematic diagram of this part of the system.

After fault clearance, there is a power oscillation between these generators and the synchronous machines from the bulk power system. This behavior is quite different from that in distributions systems with negligible or no Dispersed Generation (DG).

To estimate this parameter set, the second-order continuous transfer function formulated in (4) was used, and the constraint imposed on the GA was that only complex conjugated pairs of the poles were valid for the optimization procedure. This constraint was motivated by the oscillatory dynamics recorded after a disturbance clearance by the protection system; once that an inverse Laplace transformation of a continuous transfer function, with complex conjugated pairs of the poles, evaluates an oscillatory step response [11] and [12].

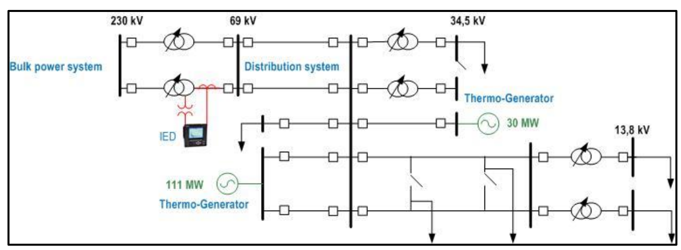

Fig. 9 – Schematic diagram of the utility to be modeled for the proposed method.

Fig. 10 presents the result of the estimated load model for active power at the analyzed bus. Once again, the red curve is the measured active power, the blue curve is the active power simulated by the proposed model shown at the top of the figure in the form of (1), although the model's parameters were found by transforming (4) into (2) with the Tustin transformation [11]. Finally, the green curve is a constant impedance model (P_{zip}), which is still used by the utility to represent the load in dynamic simulations when there is no information of the distribution grid topology.

Clearly, the constant impedance model is not able to approximate the load behavior, neither during nor after the disturbance. This generic constant impedance model is an overoptimistic load model, as defined in [5], for this type of distribution system, which means the power deviation is underestimated and may lead to a misevaluation of the stability margins and even to a voltage collapse in extreme cases.

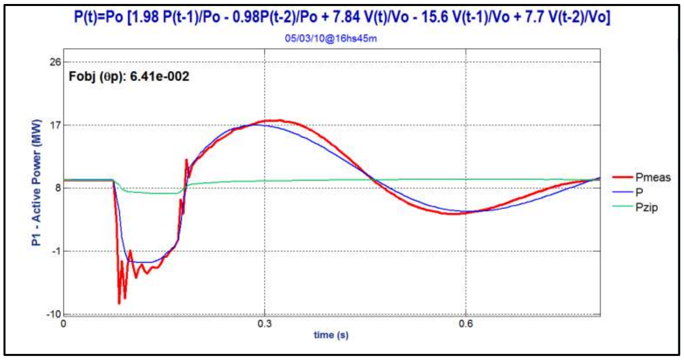

Fig. 10 – Reproducing a specific event: a distribution system containing DG and active power behavior.

Fig. 11 presents the results of the error minimization process for estimation of parameters set (3) and (5). Note that attempts to find a solution for (3) failed within 300 generations (or GA iterations), whereas the parameter estimation for (5) was successful; this parameter set was simulated and presented in Fig. 10.

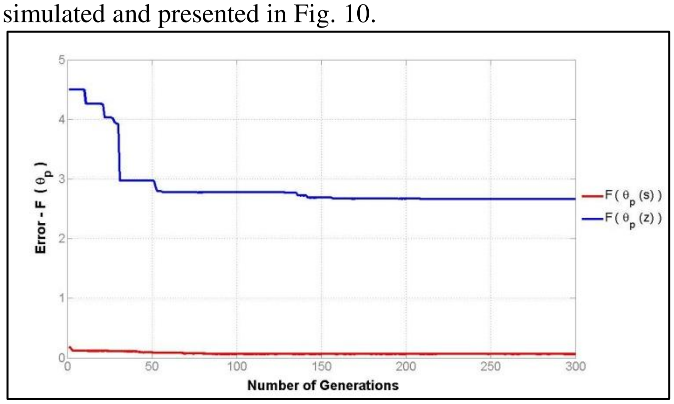

Fig. 11 - Error minimization process for the parameter estimates shown in Fig. 10.

Fig. 12 shows the reactive power curve, both measured and simulated, and the parameter set estimated for the reactive power autoregressive model (1). The reactive power expression, calculated by the parameter set, is shown at the top of the figure.

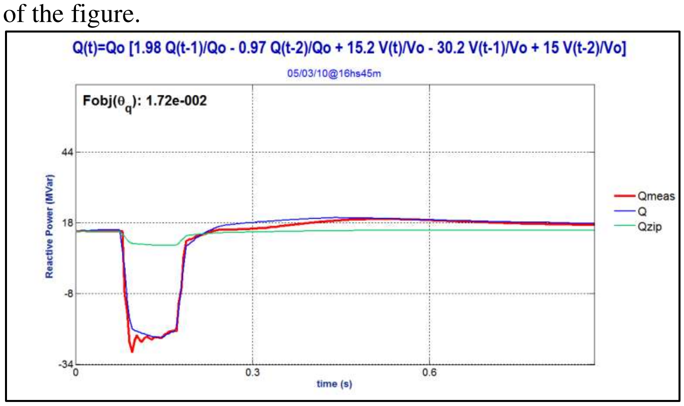

Fig. 12 – Reproducing a specific event: a distribution system containing DG and reactive-power behavior.

Once more, the constant impedance model (Q_{zip}) was not able to represent the load dynamics and the sign change of the reactive power during the fault.

Fig. 13 compares the parameter estimation performance and, once again, the parameter estimation for (5) was faster and, in the end of 300 generations, resulted in a better phenomenon.

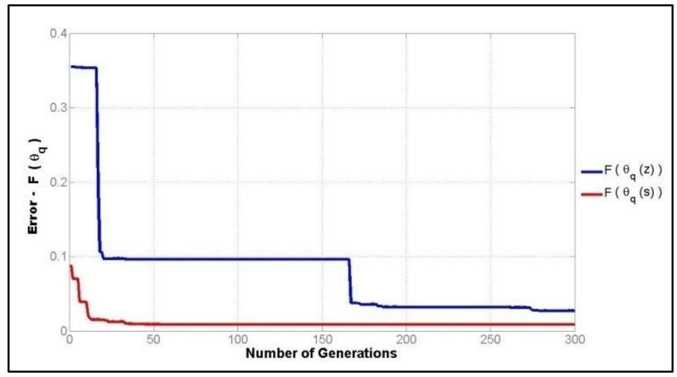

Fig. 13 - Error minimization process for the parameter estimates shown in Fig. 12.

VI. Dynamic Simulation with Estimated Models

The estimated load model for the distribution system containing DG was simulated in Anatem [14], a Brazilian transient stability simulation software, in which the entire interconnected national power system is modeled, excluding 69kV distribution systems, whose are represented by simplified generic ZIP models.

To reproduce the event, a short circuit was simulated in a nearby 230 kV transmission line, and more than 30 distribution systems were measurement-based load modeled, including the equivalent one estimated for distribution system shown in Fig. 9.

Fig. 14 and Fig. 15 respectively present the active- and reactive power curves simulated at the same 69 kV bus containing DG (Fig. 9), whose active and reactive power load models were estimated in previous section.

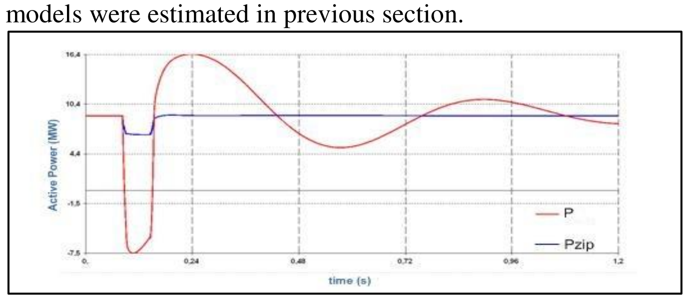

Fig. 14 – Active power simulated at the 69 kV bus bar with DG by a constant-impedance load model (**Pzip**) and the last section's estimated model (P).

Power oscillation modes clearly could not be represented by the constant impedance model. In addition, both the active and reactive power flows have changed signs during the disturbance. This result means that, for a short period of time, the distribution system injects active and reactive power into the transmission system. For reactive power, this phenomenon also happens with distribution systems without DG.

For active power, this oscillatory phenomenon post-fault clearance only occurs where there is a high penetration of DG in the distribution system. In these situations, the behavior of active power may affect some types of protective relays, load-shedding logic and special protection schemes. As a final remark, conventional ZIP models are not capable of simulating these phenomena.

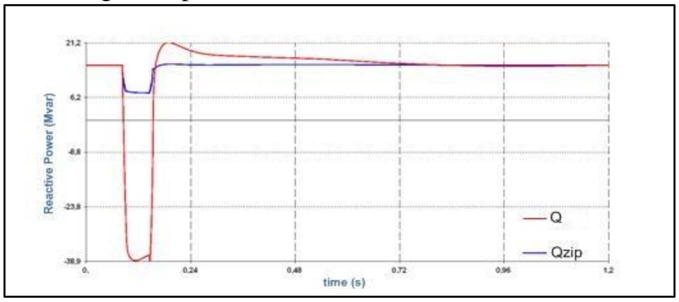

Fig. 15 – Reactive power simulated at the 69 kV bus bar with the constant-impedance (**Qzip**) and estimated models (Q).

VII. Conclusions and Future Developments

A methodology for measurement-based load modeling was used in this work to represent the equivalent load of distribution systems with and without DG. The DG may cause power oscillations that are not present in conventional distribution systems. This result can lead to problems such as protection systems failure.

It was shown that a continuous second-order transfer function was able to successfully represent active power for a wide range of steady-state load levels and for different and specific types of disturbance severities. However, reactive power load models need further investigations to aim for a more generic load model active power

Properly defining a solution search space for an optimization strategy based upon a heuristic approach is a key factor for achieving a feasible solution for a modeling problem. Although the data used in this work are sampled at discrete moments in time, these voltage and current signals are continuous in nature. Therefore, it seemed to be interesting to study both discrete and continuous transfer functions, and the results seemed to indicate that searching parameter set solutions for continuous transfer functions are more likely to achieve better results, because there is a wider search space for stable continuous transfer poles (any complex number with a negative real part is an acceptable solution) than for the discrete counterpart (any complex number with magnitude less than one is an acceptable solution).

Notably, modeling aims to describe a representation of a real system but will never establish an exact link between them. In practical terms, modeling should care about usefulness and not an unambiguous description of the truth, which is not feasible. Modeling reactive power may not be possible for a single model but may instead require two or three different parameter sets that would cover most typical situations. This is the pragmatic view modeling should pursue.

Although measurement-based load modeling has no intention to use a model structure with any physical meaning, some insights are crucial for designing model structures and for constraining the solution search space. That was the conclusion for the continuous transfer function with complex conjugated poles, which could represent the electromechanical transitory oscillation after a disturbance clearance, presented in Chapter V,.on estimating parameters for a specific contingency. Further investigations should be employed for a more flexible load model that could be accurate for different scenarios with DG embedded in distributions system, in order to model the whole system as a single power consuming element of the system

Dynamic simulation results have shown the importance of load modeling and how dangerous the reliance on a simplified load model could be for the accuracy of the results. Of course, this reliance often occurs when there is not much information about the distribution systems that are connected to the bulk power systems.

VIII. Aknowledgments

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X. Biographies

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