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Identification of Synchronous Generator Using Nonlinear Feedback Model

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Abstract: In this paper, the new approach for identification of synchronous generator using nonlinear feedback model and with piecewise linear map is investigated. In this method, synchronous generator model consists of a linear-dynamic block in forward path and a nonlinear-static block in feedback path. The identification method simultaneously approximates these blocks without requiring prior assumptions on the form of the static non-linearity. In this study, the field voltage is considered as the input and the active output power and the terminal voltage are considered as the outputs of the synchronous generator. The proposed method has been tested on a synchronous machine. Experimental results show good accuracy of the identified model.

1. INTRODUCTION

With the increased complexity of the modern interconnected power systems, analysis of the dynamic performance of such systems has become very important. For the analysis of the dynamic performance and stability of the system, a valid dynamic model is a basic requirement. For this reason, identification and modeling of different parts of the power systems, has attracted many researchers.

Synchronous generators play a very important role in the stability of the power systems. A valid model for synchronous generators is essential for a valid analysis of stability and dynamic performance. Almost three quarters of a century after the first publications in this area (Kilgore, 1931 and Wright, 1931), the subject is still a challenging and attractive research topic.

The traditional methods of modeling of synchronous generators are well specified in IEEE standards (IEEE Standard 115-1995). These methods assume a known structure for the synchronous machine, using well-established theories like Park transformation. They address the problem of finding the parameters of the known structure. Usually the procedures involve difficult and time-consuming tests. These approaches include short-circuit tests, standstill frequency response (SSFR) and open circuit frequency response (OCFR) (Karrari *et al.*, 2005). These tests can mainly be carried out when the machine is not in service.

To overcome the shortcomings of the traditional methods, identification methods based on on-line measurements have gained attention during the recent years (Melgoza *et al.*, 2001a, b, Lai *et al.*, 1996, Karrari *et al.*, 2005, Shamsoollahi *et al.*, 1996, and Sadabadi *et al.*, 2007). These methods can be divided into two categories. In the first category (Melgoza *et al.*, 2001a, b, and Lai *et al.*, 1996), assuming a known structure for the synchronous machine (as the traditional methods), the physical parameters are estimated from on-line measurements. The second category (Karrari *et al.*, 2005, Shamsoollahi *et al.*, 1996, and Sadabadi *et al.*, 2007) deals with black-box modeling of synchronous generators using input-output data. In the black-box modeling the structure of the model is not assumed to be known a priori. The only concern is to map the input data set to the output data set.

System identification using linear model structures has been extensively developed and many good approaches are available (Ljung, 1999). In practice, however, all real systems such as synchronous machines possess some non-linearity, and this non-linearity can degrade the effectiveness of linear system identification methods. Accordingly, there has been significant effort during the past several decades to develop techniques for nonlinear system identification and many different approaches, like Nonlinear Least Squares, Volterra series, Weiner series, Wavelets, Neural networks, Fuzzy logic and Genetic algorithm have been developed for identification of nonlinear systems. A survey of techniques prior to the 1980s is given in (Billings, 1980). A good recent review of the nonlinear identification approaches can be found in (Nelles, 2001).

In this paper, the aim is to identify a nonlinear black-box model for a synchronous generator using nonlinear feedback model. Nonlinear feedback model consists of a linear-dynamic block in forward path and a nonlinear-static block in feedback path (Pelt *et al.*, 2001). One of the key components of our approach is the use of piecewise linear approximations for the static non-linear blocks. Such models for synchronous generators can be used for system analysis and controller design, especially designing power systems stabilizer (PSS) (Karrari *et al.*, 2005).

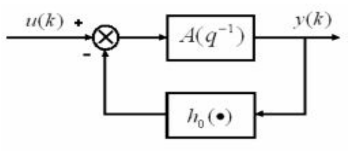

Fig. 1. Nonlinear feedback model

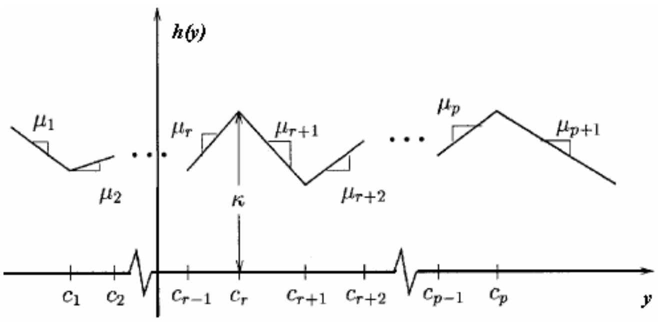

Fig. 2. Parameterization of the piecewise linear function

The paper is organized as follows: In Section 2, the identification method is described. In this Section, first the nonlinear feedback model, then point-slope parameterization for piecewise linear functions and finally the identification method are introduced. Section 3 describes the model of the system. Experimental setup and data collection on a micro-machine are discussed in Section 4. In Section 5, the application of the proposed method is carried out on the micro-machine and the experimental data is compared with the simulated nonlinear model of the synchronous generator. Section 6 concludes the paper.

2. IDENTIFICATION METHOD

2.1 Nonlinear Feedback Model

Consider the single-input single-output nonlinear feedback model shown in Fig. 1., where $u(k)$ is the input and $y(k)$ is the output of model. This model consists of a linear time-invariant (LTI) block and the static non-linearities $h_0 : \Re \rightarrow \Re$.

The LTI block is represented by the n^{th} order strictly proper transfer function.

$$A(q^{-1}) = \frac{N(q^{-1})}{D(q^{-1})} = \frac{b_1 q^{-1} + \ldots + b_n q^{-n}}{1 + a_1 q^{-1} + \ldots + a_n q^{-n}} \tag{1}$$

where q^{-1} is the backward shift operator. The output $y(k)$ is given by

$$y(k) = A(q^{-1})(u(k) - h_0(y(k))) \tag{2}$$

2.2 Parameterization of piecewise linear functions

The h_0 block can be approximate by a continuous piecewise linear function h. To represent these functions, the parameterization illustrated in Fig.2 is used.

This parameterization is characterized by the function value $\kappa = h(c_r)$ and the slope parameters $_1$, $_2$, ..., $_{p+1}$ defined over a partitioning $(-\infty, c_1], [c_1, c_2], ..., [c_p, \infty)$ of the domain of *h* (Pelt *et al.*, 2001). Let $c_1 < c_2 < \cdots < c_p$ be real numbers, let $c = [c_1 \cdots c_p]^T$ be the partition of the domain of *h,* let $_i \in \Re,\ i = 1, \ldots, p+1,\ \kappa \in \Re$ and let $r \in \{1, ..., p\}$ be the primary index at which the value $\kappa = h(c_r)$ is specified. Then *h* is represented by

$$h(y) = \begin{cases} {}_{\delta(y)}(y - c_{\delta(y)}) - \sum_{j=\delta(y)+1}^{r} {}_j(c_j - c_{j-1}) + \kappa & \delta(y) < r \\ {}_{\delta(y)}(y - c_r) + \kappa & r \le \delta(y) \le r+1 \\ {}_{\delta(y)}(y - c_{\delta(y)-1}) + \sum_{j=r+1}^{\delta(y)-1} {}_j(c_j - c_{j-1}) + \kappa & \delta(y) > r+1 \end{cases} \tag{3}$$

where

$$\delta(y) = \begin{cases} 1 & y \le c_1 \\ i & c_{i-1} < y \le c_i \quad ; \quad i = 2, ..., p \\ p+1 & c_p < y \end{cases} \tag{4}$$

By defining the slope vector

$$= [\ _1 \ \cdots \ _{p+1}]^T \in \Re^{p+1} \tag{5}$$

$h(y)$ can be written as (Pelt *et al.*, 2001)

$$h(y) = \ ^T \eta(y) + \kappa \tag{6}$$

where

$$\eta(y) = \begin{cases} \eta_1(y) & \delta(y) < r+1 \\ \eta_2(y) & \delta(y) \ge r+1 \end{cases} \tag{7}$$

and where

$$\eta_1(y) = [0_{1\ (\delta(y)-1)}\ y - c_{\delta(y)}\ c_{\delta(y)} - c_{\delta(y)-1} \cdots \\ c_{r-1} - c_r\ 0_{1\ (p+1-r)}]^T \in \Re^{P+1} \tag{8}$$

and

$$\eta_2(y) = [0_{1\ r}\ \ c_{r+1} - c_r\ \dots\ c_{\delta(y)-1} - c_{\delta(y)-2}$$
$$y - c_{\delta(y)-1}\ \ 0_{1\ (p-r+1)}]^T \in \Re^{p+1} \tag{9}$$

2.5 Nonlinear Feedback Model Identification

Consider the nonlinear feedback model in (2). The output $y(k)$, using the piecewise linear approximation h of h_0, is then given by

$$y(k) = A(q^{-1})(u(k) - h(y(k))) \tag{10}$$

which has the time series representation

$$y(k) = b_1 u(k-1) + \dots + b_n u(k-n) - b_1 h(y(k)) - \dots$$
$$- b_n h(y(k-n)) - a_1 y(k-1) - \dots - a_n y(k-n) \tag{11}$$

Noting that

$$1_{p+1}^T \eta(y) = y - c_r \tag{12}$$

Substituting (6) into (11) yields

$$y(k) = \sum_{j=1}^{n} (b_j u(k-j) - (b_j \ \ ^T + a_j 1_{p+1}^T)$$
$$\eta(y(k-j)) - a_j c_r - \kappa b_j) \tag{13}$$

Next define

$$a = [a_1\ \dots\ a_n]^T \in \Re^n$$
$$b = [b_1\ \dots\ b_n]^T \in \Re^n \tag{14}$$

Equation The (13) can further be written as follows:

$$y(k) = \theta^T \phi(k) \tag{15}$$

where

$$\theta = \begin{bmatrix} vec(\ \ b^T + 1_{p+1} a^T) \\ b \\ 1_n^T(\kappa b + c_r a) \end{bmatrix} \in \Re^{n+n(p+1)+1} \tag{16}$$

$$\phi(k) = [-\phi_\eta^T \quad \phi_u^T \quad -1]^T \in \Re^{n+n(p+1)+1} \tag{17}$$

where

$$\phi_\eta(k) = [\eta(y(k-1)) \ \ \dots \ \ \eta(y(k-n))]^T \in \Re^{n(p+1)} \tag{18}$$

$$\phi_u(k) = [u(k-1) \ \ \dots \ \ u(k-n)]^T \in \Re^n \tag{19}$$

Next consider input-output measurement $u(k)$ and $y(k)$ for $k = 0, \dots, N$, where $N \ge n$, form the least square cost function

$$J(\theta) = \|Y - \Phi\theta\|_2 \tag{20}$$

where

$$Y = [y(n)\ \cdots\ y(N)]^T \tag{21}$$

$$\Phi = \begin{bmatrix} \phi^T(n) \\ \vdots \\ \phi^T(N) \end{bmatrix} = [-\Phi_\eta \quad \Phi_u \quad -1_{N-n+1}] \tag{22}$$

where

$$\Phi_\eta = \begin{bmatrix} \phi_\eta{}^T(n) \\ \vdots \\ \phi_\eta{}^T(N) \end{bmatrix} \quad , \quad \Phi_u = \begin{bmatrix} \phi_u{}^T(n) \\ \vdots \\ \phi_u{}^T(N) \end{bmatrix} \tag{23}$$

The model output (15) is not linear in b, , and κ. Although a nonlinear least squares techniques can be used to minimize $J(\theta)$, we proceed by bounding $J(\theta)$. First, let $\theta_A \in \Re^{n(p+1)}$ and rewrite (20) as (Pelt *et al.*, 2001)

$$J(\theta) = \left\| Y - \Phi\tilde{\theta} - \Phi_\eta(\theta_A - vec(\ \ b^T + 1_{q+1} a^T)) \right\|_2 \tag{24}$$

where

$$\tilde{\theta} = \begin{bmatrix} \theta_A \\ b \\ \theta_\kappa \end{bmatrix} \in \Re^{n+n(p+1)+1} \tag{25}$$
$$\theta_\kappa = 1_n^T(\kappa b + c_r a)$$

By invoking the triangle inequality, we obtain (Pelt *et al.*, 2001)

$$J(\theta) \le J_{LS}(\tilde{\theta}) + \sigma_{\max}(\Phi_\eta)\ J_A(\ \ , a, b, \theta_A) \tag{26}$$

where

$$J_{LS}(\tilde{\theta}) = \left\| Y - \Phi\tilde{\theta} \right\|_2$$
$$J_A(v, a, b, \theta_A) = \left\| vec^{-1}(\theta_A) - (\ \ b^T + 1_{p+1} a^T) \right\|_F \tag{27}$$

where $\|.\|_F$ is the Forebenius norm, $\sigma_{\max}(.)$ is the largest singular value, $vec(.)$ and $vec^{-1}(.)$ are the column stacking operation and its inverse.

We proceed by sequentially minimizing $J_{LS}(\tilde{\theta})$ and $J_A(\ ,a,b,\theta_A)$. To do this, first determine $\tilde{\theta}$ that minimizes the linear least squares cost $J_{LS}(\tilde{\theta})$ (Pelt *et al.*, 2001). Writing

$$\hat{\tilde{\theta}} = \begin{bmatrix} \hat{\theta}_A \\ \hat{b} \\ \hat{\theta}_\kappa \end{bmatrix} \in \Re^{n+n(p+1)+1} \tag{28}$$

Then extract $\tilde{\theta}_A$ and $\hat{b}$ from $\hat{\tilde{\theta}}$ and minimize $J_A(\ ,a,\hat{b},\hat{\theta}_A)$. Assuming that $(\Phi^T\Phi)^{-1}$ exists, $J_{LS}(\tilde{\theta})$ is minimized by

$$\hat{\tilde{\theta}} = (\Phi^T\Phi)^{-1}\Phi^T Y \tag{29}$$

and thus the minimum value of $J_{LS}(\tilde{\theta})$ is given by (Pelt *et al.*, 2001)

$$J_{LS}(\hat{\tilde{\theta}}) = Y^T(I_{N-n+1} - \Phi(\Phi^T\Phi)^{-1}\Phi^T)Y \tag{30}$$

The estimates of $\hat{a}$ and $\hat{v}$ that minimize $J_A(\ ,a,\hat{b},\hat{\theta}_A)$ are given by (Pelt *et al.*, 2001)

$$\hat{a} = vec^{-T}(\hat{\theta}_A)\frac{1_{p+1}}{p+1} + \alpha\hat{b} \tag{31}$$

$$\hat{v} = (I_{p+1} - \frac{1_{p+1}1_{p+1}^T}{p+1})vec^{-1}(\hat{\theta}_A)\frac{\hat{b}}{\hat{b}^T\hat{b}} + \alpha 1_{p+1} \tag{32}$$

for an arbitrary stability parameter α. Furthermore, $\hat{\kappa}$ is given (Pelt *et al.*, 2001)

$$\hat{\kappa} = \frac{\hat{\theta}_\kappa - c_r 1_n^T\hat{a}}{1_n^T\hat{b}} \tag{33}$$

The piecewise linear least squares identification with a nonlinear feedback model is summarized as follows:

1- Collect input-output measurements $u(k)$ and $y(k)$; $k = 0, \ldots, N$, where $N \geq n$.
2- Form the regression matrix Φ and output vector Y in the equations (22) and (21).
3- Obtain $\hat{\tilde{\theta}}$ by solving the linear least squares problem given by (29).
4- Extract $\tilde{\theta}_A$ and $\hat{b}$ from $\hat{\tilde{\theta}}$.
5- Set the parameter α.
6- Compute the parameter estimates $\hat{a}$, $\hat{v}$, and $\hat{\kappa}$ using equations (31), (32), and (33).

3. SYSTEM MODEL

In most papers dealing with identification of a synchronous generator, a mathematical model of the system is given. The model is required either for estimation of its parameters or is used in simulation studies to obtain a typical input-output data. In this paper, the model presented for synchronous generator is obtained using a practical experiment on a micro-machine. The micro-machine can represent dynamic response of much larger synchronous machines when the parameters and variables are considered in a normalized version (per unit system) (Kundur, 1994).

Synchronous generator models are given in many papers and textbooks (Kundur, 1994). It is clear from the structures that a synchronous generator is a nonlinear system. If some practical nonlinearities, such as the magnetic saturation of the stator and rotor iron (which are usually ignored for simplicity) are considered, the system shows highly nonlinear properties. Therefore, a physical synchronous machine, a micro-machine in this case, represents a good challenge for any system identification technique.

The inputs of a synchronous generator are the field voltage (v_f) and the mechanical torque. Since the mechanical torque is not easily measurable and controllable, usually the field voltage is chosen as the main input of the system for identification and control. Here the field voltage (v_f) was chosen as the input of the system. The outputs of the system are electrical power (*P*) and terminal voltage (v_t).

4. EXPERIMENTAL SETUP AND DATA COLLECTION

The system under consideration is a 3 *kVA*, 208 *V*, 3 phase micro-machine, driven by a DC motor. The main problem with a micro-machine can be the field time constant, which is much lower than that of larger machines. This problem has been overcome using a time constant regulator, which is used to increase the effective field time constant of the synchronous machine to match that of larger units.

The experimental setup used for the experiment is shown in Fig. 3. The synchronous generator is driven by a DC motor.

The exciting input signal is applied to the synchronous machine through a D/A converter. The field voltage, terminal voltage and the electrical power are measured and sampled by the data acquisition system. The machine is connected to a constant voltage bus by a doubly circuit transmission line modeled by lumped elements. Each circuit consists of six π sections and simulates the performance of a 300 *kV* long 500 *kV* transmission line.

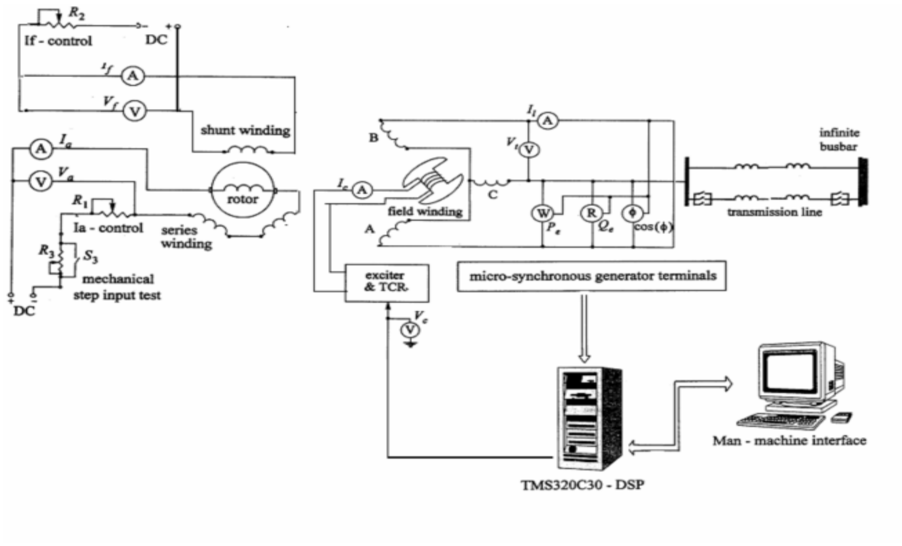

Fig. 3. Experimental setup for the micro-machine

The sampling time was selected to be 50 *ms*. This sampling time proved to be fast enough to capture the required dynamics.

In this experiment, a pseudo random binary sequence (PRBS) input was applied on the field voltage. The operating condition was selected to be P=0.6 *p.u.*, v_t =1.2 *p.u.* In this experiment, the field voltage was changed from $v_f = 1.057$ *p.u.* to $v_f = 1.4148$ *p.u.*

The field voltage, terminal voltage and the electrical power measured from the experiments are shown in Fig. 4.

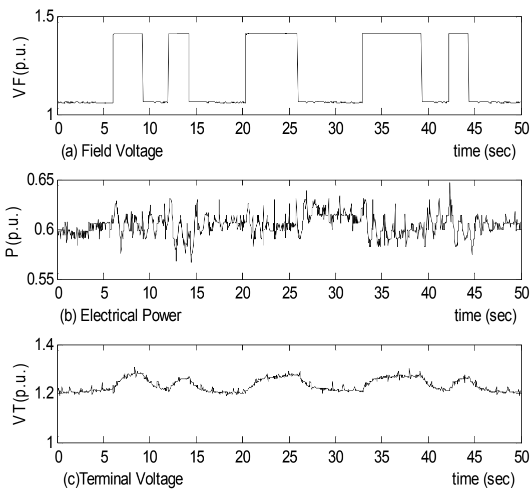

Fig. 4. Experimental data with a PRBS signal applied to the field voltage

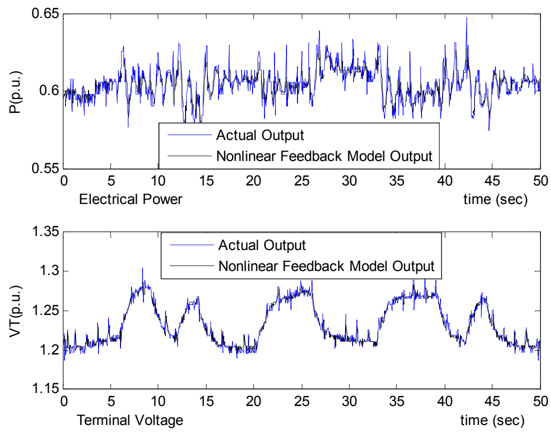

Fig. 5. Identification results with nonlinear feedback model and the measured variables

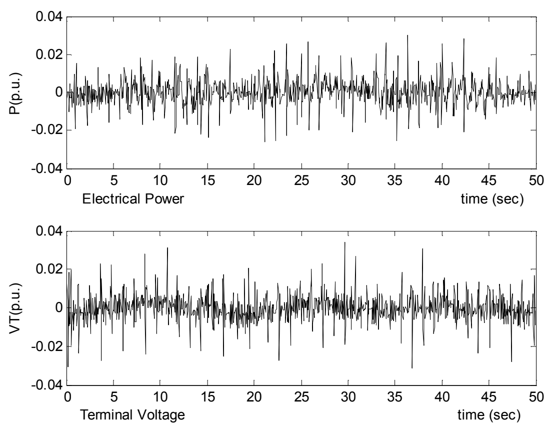

Fig. 6. The error signals of Fig. 5

5. SIMULATION RESULTS

The proposed method is used to identify the nonlinear model of a synchronous generator described in the previous section.

In these simulations, a higher order linear model offers no improvement in fitting the nonlinear feedback model. Therefore, a linear model of order $n = 2$ is considered. The parameters α , p, and r are non-unique. They were chosen to match the identified nonlinearities with the components of the simulated system.

Results of the identification by the nonlinear feedback model with the measured variables of Fig. 4., are shown in Fig. 5. and Tables 1, 2. Since the system output and the model output are not distinguishable in Fig. 5., the error signals are shown in Fig. 6. As can be seen from the figures, the proposed method is successful in identifying the micro-machine dynamics.

6. CONCLUSIONS

Nonlinear identification of synchronous generator using a nonlinear feedback model and with a piecewise linear map is described in this paper. In this method, the synchronous generator model consists of a linear-dynamic block in forward path and a nonlinear-static block in feedback path. The identification method simultaneously approximated the linear dynamic and static non-linear blocks, and did not require prior information about the form of the nonlinearity. The proposed method is classified as black-box modeling and, therefore, does not require a specific structure for the system.

In this study, the terminal voltage and the active power are considered as the outputs of the system and the field voltage as the input of the system. Simulation results show that proposed method is a powerful method for the identification of synchronous generator.

Table 1. Nonlinear Feedback Model Coefficients (Input Signal: Field Voltage, Output Signal: Electrical Power)

$n = 2, p = 2, r = 2, \alpha = -0.5$

Coefficient of Linear Model: $A(q^{-1}) = \dfrac{0.0134\,z^{-1} - 0.0167\,z^{-2}}{1 - 0.551\,z^{-1} - 0.096\,z^{-2}}$
Coefficient of Nonlinear Model ($h(y)$): $= [-5.583 \quad -10.096 \quad 14.179]$ $\kappa =$ -3.0167

Table 2. Nonlinear Feedback Model Coefficients (Input Signal: Field Voltage, Output Signal: Terminal Voltage)

$n = 2, p = 5, r = 2, \alpha = -1.5$

Coefficient of Linear Model: $A(q^{-1}) = \dfrac{0.0041\,z^{-1} + 0.015\,z^{-2}}{1 - 0.391\,z^{-1} - 0.720\,z^{-2}}$
Coefficient of Nonlinear Model ($h(y)$): $= [36.31 \ -76.81 \ 51.07 \ -25.195 \ -14.557 \ 20.177]$ $\kappa = 1.364$

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