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Authors: **Ahmad Boussoufa, Madjid Kidouche, Aimad Ahriche**

Affiliations**:**
Applied Automation Laboratory, University of Boumerdes (LAA), Boumerdes, Algeria

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Laboratory of Signals and Systems
Address : IGEE (Ex-INELEC), Boumerdes University, Avenue de l'indépendance, 35000, Boumerdes, Algeria
Phone/Fax : 024 79 57 66
Email : lss@univ-boumerdes.dz ; ajsyssig@gmail.com

Rotor Speed and Flux Estimation of a Doubly-fed Induction Machine Using Extended Kalman Filter

Ahmad Boussoufa*, Madjid Kidouche, Aimad Ahriche

Applied Automation Laboratory, University of Boumerdes (LAA), Boumerdes, Algeria
*Email: boussoufa.ah@gmail.com

Abstract: This paper uses Extended Kalman Filtering method (EKF) to estimate the rotor speed and flux of a Doubly-fed Induction Generator (DFIG) to be used in Wind Turbines (WTs). DFIGs are widely used in WTs because they can generate an electric power of constant voltage amplitude and frequency which allow a direct connection between the WTs and the ac power network. A DFIG modeling in the (dq) reference frame is presented and a brief description of EKF algorithm is described to estimate the rotor speed and flux. Simulations results are shown and discussed.

Keywords: Doubly-fed induction machine**,** dq-reference model, state estimation, Kalman filter.

1. INTRODUCTION

Doubly-fed induction generators (DFIGs) are by far the most common and widely used type of generators to produce electricity in wind turbines. They have more advantages over other types of generators when used in wind turbines. Their main benefit is that they allow the wind turbines to generate an electric power of constant voltage amplitude and frequency despite variations in the generator rotor speed caused by fluctuations of the mechanical power provided by the prime mover (e.g., a wind turbine rotor) driving the generator. To achieve this purpose, the frequency of the ac currents fed into the rotor windings of the DFIG must be continually adjusted to counteract any variation in the rotor speed induced by the variation of the mechanical power provided by the prime mover driving the generator [1,2,3]. Several methods have been applied to estimate the states of the DFIG machine, a comparison between three popular methods: extended Kalman filter (EKF), particle filter (PF) and unscented Kalman filter (UKF) is presented in [10].

In this paper, we will develop a dynamic model of the DFIG in the dq reference frame. The model is then used to estimate the rotor speed and flux using EKF. A detailed description of the EKF algorithm is presented, results of simulation are shown and discussed.

2. DYNAMIC MODEL OF THE DFIG

To develop a state space estimator of the DFIG, a dynamic model is needed. The construction of a DFIG is similar to a wound rotor induction machine (IM) and comprises a three-phase stator winding and a three-phase rotor winding [4,5,6]. The latter is fed via slip rings by an AC voltage. The voltage equations of both stator and rotor referred to their natural reference frames are given by:

$$\begin{cases} v_{as} = R_s i_{as} + \dfrac{d\psi_{as}}{dt} \\ v_{bs} = R_s i_{bs} + \dfrac{d\psi_{bs}}{dt} \\ v_{cs} = R_s i_{cs} + \dfrac{d\psi_{cs}}{dt} \end{cases} \tag{1}$$

$$\begin{cases} v_{ar} = R_r i_{ar} + \dfrac{d\psi_{ar}}{dt} \\ v_{br} = R_r i_{br} + \dfrac{d\psi_{br}}{dt} \\ v_{cr} = R_r i_{cr} + \dfrac{d\psi_{cr}}{dt} \end{cases} \quad (2)$$

where:

$\psi_{as}, \psi_{bs}, \psi_{cs}$: fluxes of the three phases of the stator.

$\psi_{ar}, \psi_{br}, \psi_{cr}$: fluxes of the three phases of the rotor.

Transforming these equations from three-phase to two-phase components $(\alpha\beta)$ and subsequently rotating all variables into a synchronous reference (dq) frame as represented in $Fig.1$ yields to the following equations

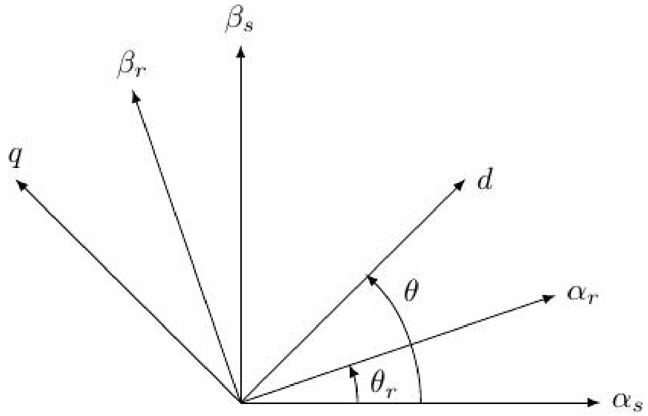

Fig. 1 the dq reference frame

$$\begin{cases} v_{ds} = R_s i_{ds} + \dfrac{d\psi_{ds}}{dt} - \omega\psi_{qs} \\ v_{qs} = R_s i_{qs} + \dfrac{d\psi_{qs}}{dt} + \omega\psi_{ds} \\ v_{dr} = R_r i_{dr} + \dfrac{d\psi_{dr}}{dt} - (\omega - \omega_r)\psi_{qr} \\ v_{qr} = R_r i_{qr} + \dfrac{d\psi_{qr}}{dt} + (\omega - \omega_r)\psi_{dr} \end{cases} \quad (3)$$

where:

$$\begin{cases} \psi_{ds} = L_s i_{ds} + L_m i_{dr} \\ \psi_{qs} = L_s i_{qs} + L_m i_{qr} \\ \psi_{dr} = L_m i_{ds} + L_r i_{dr} \\ \psi_{qr} = L_m i_{qs} + L_r i_{qr} \end{cases} \quad (4)$$

with: $\omega = \dfrac{d\theta}{dt}$ and $\omega_r = \dfrac{d\theta_r}{dt}$.

The equation of the mechanical torque of the DFIG machine is given by:

$$T_m = T_{em} + J\frac{d\omega_r}{dt} + B\omega_r \tag{5}$$

The developed electromagnetic torque in terms of stator current and rotor flux components can be expressed as:

$$T_{em} = \frac{pL_m}{L_r}(\psi_{dr} i_{qs} - \psi_{qr} i_{ds}) \tag{6}$$

Choosing a state vector $\underline{x} = \begin{bmatrix} \psi_{ds} & \psi_{qs} & i_{dr} & i_{qr} & \omega_r \end{bmatrix}^T$, and by combining these previous equations, we obtain the following state-space representation:

$$\begin{pmatrix} \dot{\psi}_{dr} \\ \dot{\psi}_{qr} \\ \dot{i}_{ds} \\ \dot{i}_{qs} \\ \dot{\omega}_r \end{pmatrix} = \begin{bmatrix} -\frac{R_r}{L_r}\psi_{dr} + (\omega - \omega_r)\psi_{qr} + \frac{R_r L_m}{L_r} i_{ds} \\ -(\omega - \omega_r)\psi_{dr} - \frac{R_r}{L_r}\psi_{qr} + \frac{R_r L_m}{L_r} i_{qs} \\ \frac{R_r L_m}{\sigma L_r^2 L_s}\psi_{dr} - \frac{L_m}{\sigma L_s L_r}\omega_r \psi_{qr} - \frac{R_r L_m^2 + R_s L_r^2}{\sigma L_r^2 L_s} i_{ds} + \omega i_{qs} \\ \frac{L_m}{\sigma L_s L_r}\omega_r \psi_{dr} + \frac{R_s L_m}{\sigma L_r^2 L_s}\psi_{qr} - \omega i_{ds} - \frac{R_r L_m^2 + R_s L_r^2}{\sigma L_r^2 L_s} i_{qs} \\ \frac{pL_m}{JL_r}(\psi_{dr} i_{qs} - \psi_{qr} i_{ds}) - \frac{B}{J}\omega_r \end{bmatrix}$$

$$+ \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ \frac{L_m}{\sigma L_s L_r} & 0 & \frac{1}{\sigma L_s} & 0 & 0 \\ 0 & \frac{L_m}{\sigma L_s L_r} & 0 & \frac{1}{\sigma L_s} & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{J} \end{bmatrix} \begin{pmatrix} v_{dr} \\ v_{qr} \\ v_{ds} \\ v_{qs} \\ T_m \end{pmatrix} \tag{7}$$

which is of the form:

$$\dot{\underline{x}} = f(\underline{x}) + B\underline{u}$$

where : $\underline{u} = \begin{bmatrix} v_{dr} & v_{qr} & v_{ds} & v_{qs} & T_m \end{bmatrix}^T$

The output or measurement vector is:

$$\underline{z} = \begin{bmatrix} i_{ds} & i_{qs} \end{bmatrix}^T = C\underline{x} \tag{8}$$

with: $C = \begin{bmatrix} 0 & 0 & 1 & 1 & 0 \end{bmatrix}$

3. EXTENDED KALMAN FILTER

Kalman filter (KF) is one of the most used algorithm for state estimation in dynamical system. It is a recursive algorithm which estimates the non measured states based on the information given by the state-space model and the measured states [9,10]. Extended Kalman filter is a generalization of the classical KF to be used for nonlinear systems. As the classical KF, EKF consists of two steps: a prediction step and a correction step. In addition, the nonlinear system must be linearized at each iteration in order to be able to calculate the state matrix [11,12].

The Kalman filter applies the minimum mean square error (MMSE) estimation criteria to a dynamic system where we suppose that the model is not precise and is affected by random process noise vector w_{k-1} and the measurements are noisy and altered by a random noise vector v_k .

Both w_{k-1} and v_k are assumed to be independent, Gaussian noise processes of zero means and covariance matrices $\Sigma_{\tilde{w}}$ and $\Sigma_{\tilde{v}}$ respectively [13,14,15].

The discretization of DFIG nonlinear state space model using Forward Euler's method yields to the following nonlinear discrete-time state-space representation:

$$\underline{x}_k = \underline{x}_{k-1} + \Delta t f(\underline{x}_{k-1}) + B_d \underline{u}_{k-1} \tag{9}$$

where: $B_d = B\Delta t$

The following chart summarizes the EKF algorithm:

Nonlinear state-space model:

$$\begin{cases} x_k = x_{k-1} + \Delta t f(x_{k-1}) + B_d u_{k-1} + w_{k-1} \\ z_k = Cx_k + v_k \end{cases}$$

Initialization:

$$\hat{x}_0^+ = E[x_0]$$

$$\Sigma_{\tilde{x},0}^+ = E[(x_0 - \hat{x}_0^+)(x_0 - \hat{x}_0^+)^T]$$

Computation: For $k = 1, 2, \ldots$ **compute:**

Linearization:

$$A_{k-1} = \frac{df(x_{k-1})}{dx_{k-1}}$$

$$A_d = I + \Delta t A_{k-1}$$

Prediction:

$$\hat{x}_k^- = \hat{x}_{k-1}^+ + \Delta t f(\hat{x}_{k-1}^+) + B_d u_{k-1} + w_{k-1}$$

$$\Sigma_{\tilde{x},k}^- = A_d \Sigma_{\tilde{x},k-1}^+ A_d^T + \Sigma_{\tilde{w}}$$

$$\hat{z}_k = C\hat{x}_k^- + v_k$$

Correction:

$$L_k = \Sigma_{\tilde{x},k}^- C^T [C\Sigma_{\tilde{x},k}^- C^T + \Sigma_{\tilde{v}}]^{-1}$$

$$\hat{x}_k^+ = \hat{x}_k^- + L_k(z - \hat{z}_k)$$

$$\Sigma_{\tilde{x},k}^+ = (I - L_k C)\Sigma_{\tilde{x},k}^-$$

4. SIMULATION AND RESULTS

Table 1 shows the DFIG ratings used for the simulation.

Table 1 DFIG Ratings

Parameter	Value
Rated power	**3 kW**
R_s	**2.0 Ohms**
R_r	**1.78 Ohms**
L_s	**0.2406 H**
L_r	**0.2406 H**
L_m	**0.2304 H**
pole pairs	**2**
moment of inertia	**0.0408 kg.m^2**

The input mechanical torque T_m used for the simulation is set to be variable to mimic the reality in which case the speed of wind blowing at the turbine blades is variable.

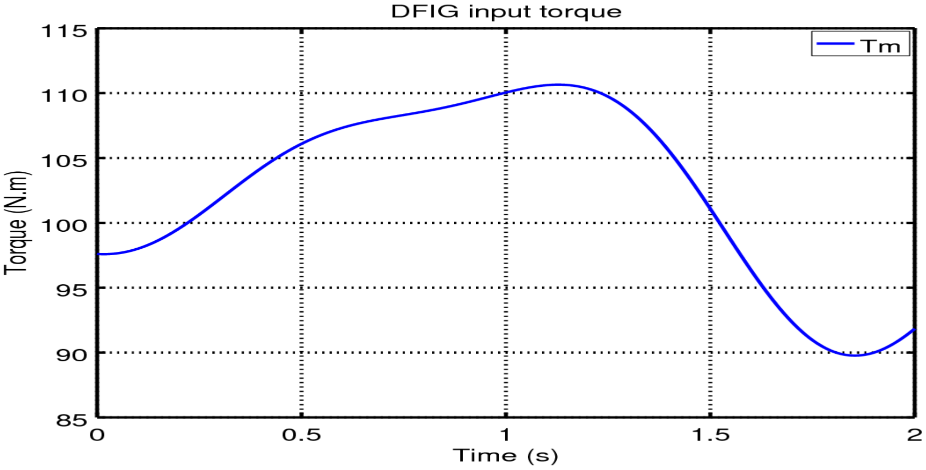

Fig. 2 Input mechanical torque of the DFIG

The measured variables i_{ds} and i_{qs} are obtained by solving the discrete nonlinear equations using the Runge-Kutta algorithm.

Adding a measurement noise of a covariance matrix :

$$\Sigma_{\tilde{v}} = \begin{bmatrix} \sigma_{v_1}^2 & 0 \\ 0 & \sigma_{v_2}^2 \end{bmatrix} = \begin{bmatrix} 10^{-1} & 0 \\ 0 & 10^{-1} \end{bmatrix} \quad (10)$$

The covariance matrix of the process noise is given by:

$$\Sigma_{\tilde{w}} = \begin{bmatrix} \sigma_{w_1}^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_{w_2}^2 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{w_3}^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{w_4}^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{w_5}^2 \end{bmatrix} = \begin{bmatrix} 10^{-1} & 0 & 0 & 0 & 0 \\ 0 & 10^{-1} & 0 & 0 & 0 \\ 0 & 0 & 10^{-1} & 0 & 0 \\ 0 & 0 & 0 & 10^{-1} & 0 \\ 0 & 0 & 0 & 0 & 10^{-1} \end{bmatrix} \quad (11)$$

Figure 3 depicts the (dq) stator currents of DFIG:

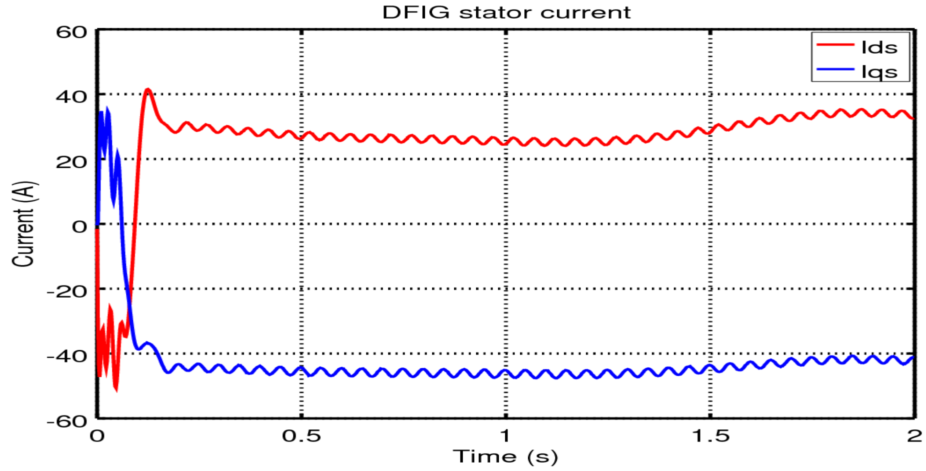

Fig. 3 stator currents of the DFIG

The estimated and actual rotor speeds are shown in Fig. 4.

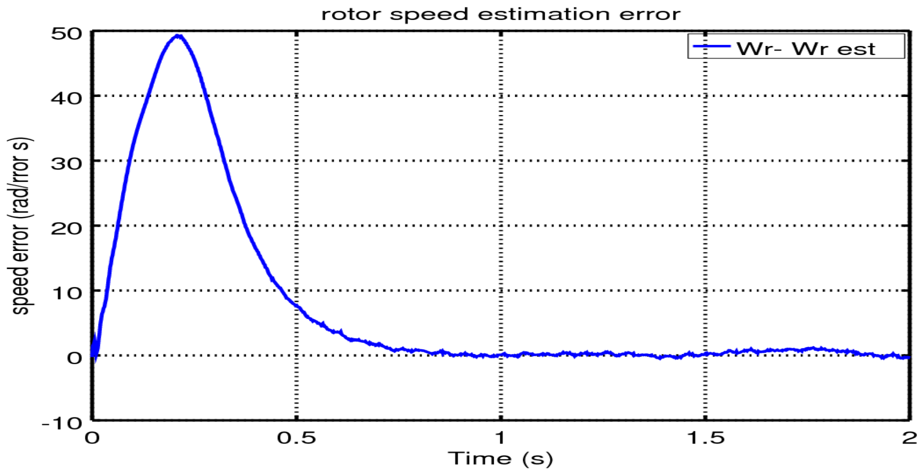

Fig. 4 rotor speed of the DFIG

From Fig. 4 we can see that the rotor speed is well estimated with a small error in the steady state regime.

The result of rotor flux estimation is shown in Fig. 5 and Fig. 6 in comparison with the simulated flux.

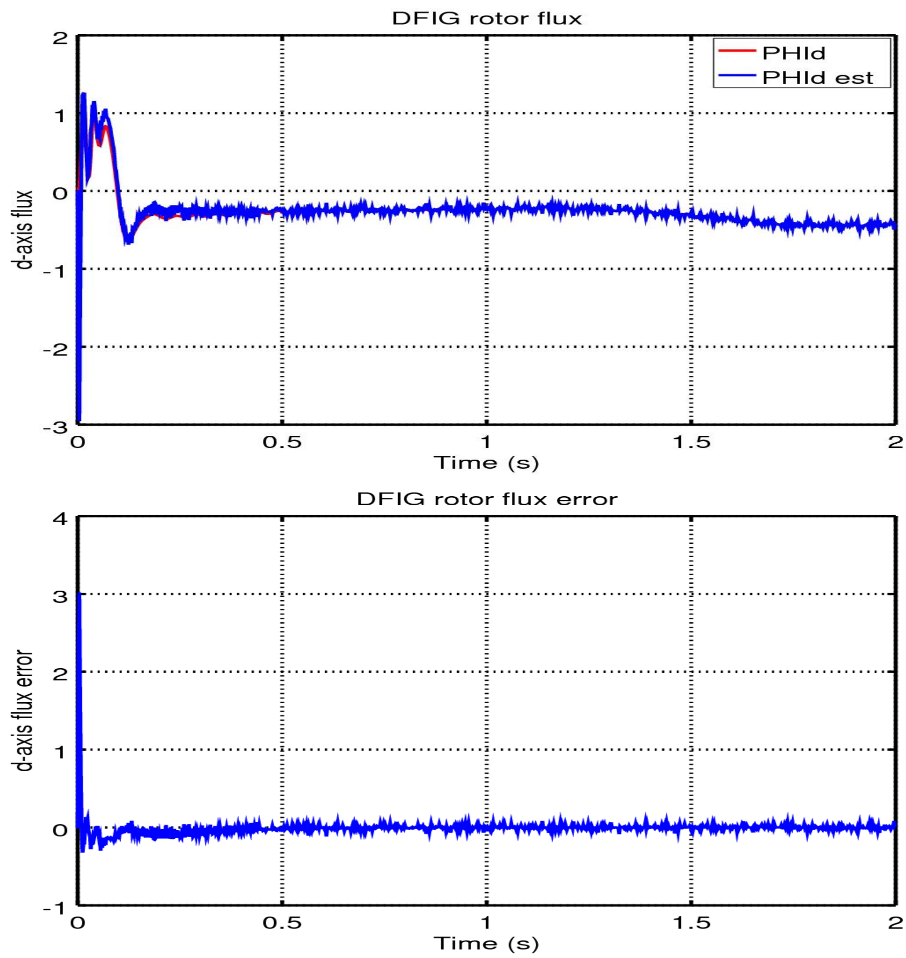

Fig. 5 d-component of DFIG rotor flux

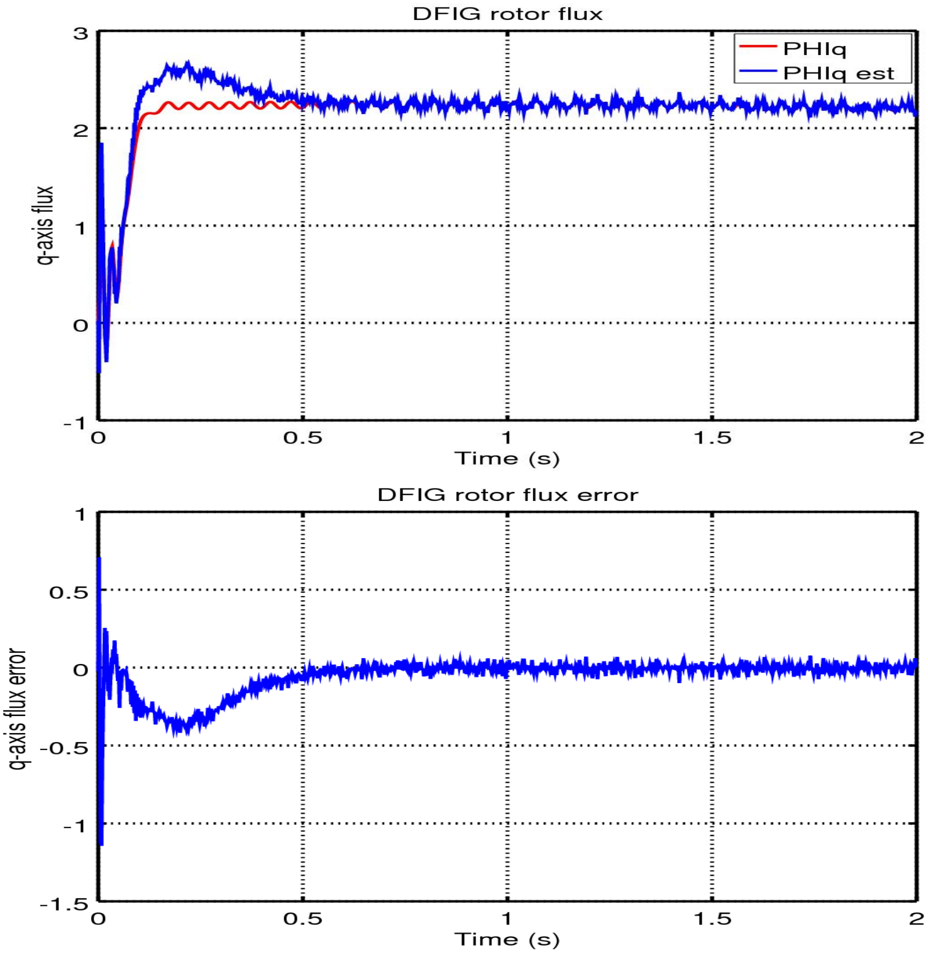

Fig. 6 q-component of DFIG rotor flux

As seen in Fig. 5 and Fig. 6, the estimation of the d-component rotor flux is a bit noisy.

5. CONCLUSION

In this paper, the rotor speed and flux of a doubly fed induction generator have been estimated using extended kalman filter. A dynamic model of the DFIG in the (dq) reference frame was derived form the mechanical and the electrical equations that describe the DFIG machine. Simulation results shows that the speed was well estimated while the estimation of rotor flux was somehow noisy.

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