ORIGINAL ARTICLE

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LOPES, Leonardo de Magalhães. PEIXOTO, Zélia Myriam Assis. An Extended Kalman Filter, with pre-adjusted covariance matrices, applied to the sensorless speed control of three-phase induction motors. Revista Científica Multidisciplinar Núcleo do Conhecimento. Year 05, Ed. 09, Vol. 02, pp. 109-126. September 2020. ISSN: 2448-0959, Access Link: <https://www.nucleodoconhecimento.com.br/electrical-engineering/kalman-filter>, DOI: 10.32749/nucleodoconhecimento.com.br/electrical-engineering/kalman-filter

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SUMMARY

With the emergence of sensorless control methods, there was a need for the use of estimators and/or state observers to give it the robustness and precision required in the drive of induction motors. This work deals with the application of the Extended Kalman Filter (EKF)

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in the estimation of rotor speed and position, aiming at the implementation of the indirect vector control technique in a sensorless speed control system for three-phase induction motors. The mathematical development of the system state variables associated with the EKF stochastic process is presented in this study, and point out its application under variable speed and load conditions, which are imposed on these motors in everyday life. The sensorless control strategy was tested through routine lines in the Matlab® software, simulating operating conditions of this type of engine, being proven its performance, as well as the convergence times consistent with the usual requirements of high performance systems. The main contributions of this work are the use of a reduced-order EKF (ROEKF) and the preset of covariance matrices to accelerate convergence in speed and position estimates for future implementations in currently accessible digital signal processors.

Keywords: EKF, Extended Kalman Filter, Induction Motors, *Sensorless*, AC electric drive systems.

1. INTRODUCTION

In recent decades, the applications of alternating current (AC) drive systems, associated with vector control techniques with speed and/or position monitoring by means of electromechanical sensors, have established themselves as a low cost alternative, greater mechanical robustness and high performance, equating to the CC drives precursors. However, the use of electromechanical transducers still includes limitations regarding maintenance costs, reliability, mechanical robustness and restrictions on operation in harsh environments (DADKHAH *et al.*, 2015).

In this context and from the emergence of digital high-speed signal processors, the systems of speed control and/or sensorless position, although they imply the increase in the mathematical and computational complexity of the control models, have been increasingly used as they contribute to the mechanical robustness and variation of machine parameters and uncertainties intrinsic to the measurements of electrical signals (BARUT *et al.*, 2008).

Several studies have been developed aiming at sensorless systems, where the sliding mode technique, adaptive systems by reference model (*Model Reference Adaptive System*) and

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Extended Kalman Filter (EKF – *Extend Kalman Filter*), among others (VIEIRA *et al.*, 2014).

Rudolf Emil Kalman presented, in 1960, a recursive solution to the problem of discrete linear filtering from the model in the space of states plus stochastic plots referring to measurement noises and modeling errors. However, the initial version of the Kalman Filter (KF – *Kalman Filter*) has limitations in relation to nonlinear characteristics such as induction motors (IM), nonlinearities related to

relationship between electromagnetic velocity and flows as well as the presence of time-varying parameters associated with these variables (BARUT *et al.*, 2007).

An alternative to KF is the Extended Kalman Filter (EKF) whose structure can be applied to linearized systems around a specific point of operation. Other variants of the Kalman Filter are available, such as the *Unscented Kalman Filter* (UKF) Akin *et al.* (2003), the EKF Combined S. Bogosyan and Gokasan (2007), *Bi Input-extended Kalman Filter* (Bi-EKF), among others.

In Barut (2010), the UKF is associated with the nonlinear model of MI and a method of filtering the covariance matrix. This combination generated the SRUKF (*Square Root UKF*), with improvements in accuracy compared to the UKF version.

In Jafarzadeh *et al.* (2013), the real-time implementation of the full-order EKF estimator with double input or Bi-EKF is described. The Bi-EKF is based on two mathematical models, one for the stator flow and the other for the rotor flow in the stationary frame, providing the complete estimation of all induction motor states in conjunction with the stator and rotor resistances, in a wide speed range (BARUT *et al.*, 2012).

Another method derived from EKF is the Reduced-Order Extended Kalman Filter (ROEKF) which, with fewer variables, provides the reduction of processing time and estimation errors without compromising system performance (YIN *et al.*, 2013) (LEITE *et al.*, 2004).

The estimation of the speed/position of IM requires the knowledge of the voltages and currents of the stator, but the total number of variables and parameters to be treated can extend up to 10, making online processing impossible. It is worth noting that the accuracy of the estimates of the control variables depends heavily on the parameters of MI and the signal

noise ratio (SNR) of the measured signals (LEITE et al., 2004).

This work proposes the application of a Reduced Order Extended Kalman Filter, especially a 5th order ROEKF, for estimating the speed and position of a three-phase induction motor based on the orthogonal components of the stator current and rotor flow.

Aiming at reducing processing time and future implementation using the Texas Instrument Manufacturer's digital signal processor, model TMDSHVMTRPFCKIT, an alternative to the 6th and 7th orders EKFs usually applied that include stator current components, rotor electromagnetic flows and stator and rotor resistances (DADKHAH *et al.*, 2015) (BOGOSYAN and GOKASAN, 2007) (BARUT, 2010) (BARUT *et al.*, 2012).

The main contributions of this work refer to the ROEKF analyses in relation to the accuracy and convergence of the speed estimation under different operating and load conditions as well as the adaptation, development and testing of the techniques of off-line tuning of the covariance matrices of the modeling errors and measurements.

2. THEORETICAL FRAMEWORK

In this section will be presented the fundamental concepts related to the mathematical model of three-phase MI, Extended Kalman Filter and offline tuning techniques of the covariance matrices, necessary for the development of the 5th order ROEKF for application in a sensorless velocity control system (AMEID *et al.*, 2016).

2.1 THE MATHEMATICAL MODEL OF THE THREE-PHASE INDUCTION MOTOR – MI

The mathematical model of MI can be described, in the stationary reference, by the components of the stator current

$$i_{\alpha_s}, i_{\beta_s}$$

and rotor flow and rotor

$$\phi_{\alpha_r}, \phi_{\beta_r}$$

and rotor speed

$$\omega_r$$

, according to equations 1 to 3 (KRAUSE *et al.*, 2013):

$$\begin{bmatrix} i_{\alpha_s} \\ i_{\beta_s} \\ \phi_{\alpha_r} \\ \phi_{\beta_r} \\ \omega_r \end{bmatrix} = A \begin{bmatrix} i_{\alpha_s} \\ i_{\beta_s} \\ \phi_{\alpha_r} \\ \phi_{\beta_r} \\ \omega_r \end{bmatrix} + \begin{bmatrix} \frac{1}{\sigma L_s} & 0 \\ 0 & \frac{1}{\sigma L_s} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_{\alpha_s} \\ v_{\beta_s} \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} i_{\alpha_s} \\ i_{\beta_s} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} i_{\alpha_s} \\ i_{\beta_s} \\ \phi_{\alpha_r} \\ \phi_{\beta_r} \\ \omega_r \end{bmatrix} \quad (2)$$

$$A = \begin{bmatrix} -a_1 & 0 & a_2 & a_3 \frac{n_p}{2} \omega_r & 0 \\ 0 & -a_1 & -a_3 \frac{n_p}{2} \omega_r & a_2 & 0 \\ a_4 & 0 & -a_5 & -\frac{n_p}{2} \omega_r & 0 \\ 0 & a_4 & \frac{n_p}{2} \omega_r & -a_5 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (3)$$

$$\text{onde } a_1 = \left(\frac{R_s}{\sigma L_s} + \frac{1-\sigma}{\sigma \tau_r} \right), a_2 = \frac{L_m}{\sigma L_s L_r \tau_r}, a_3 = \frac{L_m}{\sigma L_s L_r}, a_4 = \frac{L_m}{\tau_r}, \text{ e } a_5 = \frac{1}{\tau_r}.$$

2.2 THE EXTENDED KALMAN FILTER - EKF

The EKF is based on the continuous version of the Kalman Filter, represented by the following
barut discrete $x(k) = A_d x(k-1) - B_d u(k-1) + w(k-1)$ (4) ions
(2010): Where A_d and B_d are, respectively, the discrete arrays of parameters and process

inputs, and W contains the plots related to system modeling errors.

The equation of the measuring variable $z(k)$ is given by:

$$z(k) = Hx(k) + v(k) \quad (5)$$

H being the observation matrix and $v(k)$, the measurement noise. Both $w(k)$ and $v(k)$ are white noises with zero mean, independent of each other and with normal probability distribution. Kalman's estimator presents two steps for estimation, prediction and correction. In the prediction stage, one should predict the projection of the state in the forward step

$$\hat{x}_{(k)}^-$$

, as well as the uncertainty in the estimation

$$P_{(k)}^-$$

.

$$\hat{x}_{(k)}^- = A_d \hat{x}_{(k-1)} - B_d u_{(k-1)} \quad (6)$$

$$P_{(k)}^- = A_d P_{(k-1)} A_d^T + Q \quad (7)$$

$$P_{(k)}^-$$

is the covariance matrix of the estimator error in the instant before the current observation,

$$A_d^T$$

is the transposition of the discrete matrix of parameters and Q is the covariance matrix of the process noises.

The correction step, necessary to achieve the estimated state, is formulated

$$\hat{x}_{(k)}$$

through an equation that associates the estimated state in the prediction of the measure with

the difference between the measured actual value and the predicted value. In the correction stage, you have the equations of updating the measurement as

$$\hat{x}_{(k)}^-$$

well as the uncertainty of the estimation

$$P_{(k)}^-$$

.

$$\hat{x}_{(k)} = \hat{x}_{(k)}^- + K_{(k)}(z_{(k)} - H\hat{x}_{(k)}^-) \quad (8)$$

$$P_{(k)} = (I - K_{(k)}H)P_{(k)}^- \quad (9)$$

Where $P(k)$ is the covariance matrix of the current estimation error and I is the identity matrix.

The difference

$$(z_{(k)} - H\hat{x}_{(k)}^-)$$

indicates the divergence between the estimated a priori measure and the current measure $z(k)$. The K matrix, called the Kalman Filter earnings matrix, makes it possible to minimize the covariance of the process error and is represented by:

$$K_{(k)} = \frac{P_{(k)}^- H^T}{H P_{(k)}^- H^T + R} \quad (10)$$

Recursively, the process is repeated from the estimated results a *posteriori* in the search for the prediction of a *priori* states.

Based on the KF version, the Extended Kalman Filter is a stochastic observer that uses noise-corrupted signals indicated for the estimation of variables in nonlinear systems represented by function f , being described generically according to equations (11) and (12):

$$x(k) = f[x(k-1), u(k-1), w(k-1)] \quad (11)$$

$$z(k) = h[x(k), v(k)] \quad (12)$$

As the noises $w(k-1)$ and $v(k)$ are not known at each step, the state vectors and measurements are approximate, considering $w(k-1) = 0$ and $v(k) = 0$ (BARUT *et al.*, 2012):

$$\hat{x}(k) = f[\hat{x}(k-1), u(k-1), 0] \quad (13)$$

$$\hat{z}(k) = h[\hat{x}(k), 0] \quad (14)$$

The equations linearized through the functions F and H are Jacobian matrices calculated at each time interval. Similarly to KF equations, the steps of predicting and updating EKF

$$\hat{x}_{(k)}^- = f[\hat{x}_{(k-1)}^-, u_{(k-1)}, 0] \quad (15)$$

$$P_{(k)}^- = F_{(k)} P_{(k-1)} F_{(k)}^T + Q_{(k)} \quad (16)$$

measurements are written as:

$$\hat{x}_{(k)} = \hat{x}_{(k)}^- + K_{(k)} [z_{(k)} - H \hat{x}_{(k)}^-, 0] \quad (17)$$

$$P_{(k)} = (I - K_{(k)} H_{(k)}) P_{(k)}^- \quad (18)$$

The filter gain is then calculated as:

$$K_{(k)} = \frac{P_{(k)}^- H_{(k)}^T}{H_{(k)} P_{(k)}^- H_{(k)}^T + V_{(k)} R_{(k)} V_{(k)}^T} \quad (19)$$

3. DEVELOPMENT

3.1 EKF APPLICATION TO INDUCTION MOTOR CONTROL

Figure 1 shows the sensorless speed control system associated with the Reduced Order Extended Kalman Filter. The proposed velocity control system is based on the indirect field oriented control (IFOC) technique, which presupposes the knowledge of rotor speed and position for transformations between reference axis systems, stator stress decoupling meshes and PI controllers used (LI and ZHONG, 2005).

Thus, the state vector to be estimated by ROEKF should be composed as:

$$\hat{x}(k) = [\hat{i}_{\alpha_s}(k), \hat{i}_{\beta_s}(k), \hat{\phi}_{\alpha_r}(k), \hat{\phi}_{\beta_r}(k), \hat{\omega}_r(k)]^T \quad (20)$$

Where the angle of the magnetic flow vector of the rotor and the estimated velocity

$$\hat{\omega}_r$$

$$\hat{\theta}_{e_{kalman}} = \arctan\left(\frac{\hat{\phi}_{\beta_r}}{\hat{\phi}_{\alpha_r}}\right) \quad (21)$$

$$\hat{\omega}_r = \frac{d\hat{\theta}_{e_{kalman}}}{dt} \quad (22)$$

are calculated (EL-HALIM *et al.*, 2012):

The main steps for the implementation of sensorless induction motor drive systems, using the ROEKF algorithm, are as follows (EL-HALIM *et al.* 2012):

- Selection of the discrete induction machine model;
- Initialization of covariance matrices Q, P and R;
- Implementation of the ROEKF algorithm.

Figure 1. IFOC sensorless vector control with ROEKF speed estimator.

An Extended Kalman Filter, with pre-adjusted covariance matrices, applied to the sensorless speed control of three-phase induction motors

Source: The author adapted from Shi et al.(2002)

The diagram in Figure 2 presents the EKF operating steps.

Figure 2. EKF Operation Flowchart – Prediction and Correction Steps.

An Extended Kalman Filter, with pre-adjusted covariance matrices, applied to the sensorless speed control of three-phase induction motors

Source: The author adapted from Leite et al. (2004).

Initially, the initialization of the estimates

$$\hat{x}_{(k-1)}^-$$

and the covariance matrix of $p(k-1)$ errors are performed. Then, the update or projection of a step ahead of the state

$$\hat{x}_{(k)}^-$$

and covariance of the errors of the estimates

$$\hat{P}_{(k)}^-$$

, in the present state, is obtained from the array of engine parameters A_d and inputs B_d and $u(k-1)$.

The Covariance Matrices P , Q and R , present in the process steps, are initialized according to the predisposition to uncertainties of the estimation process of the selected state variables.

The correction is made by the difference between the actual measured value and the predicted value. This difference is minimized by the action of the K gain on the estimate

$$\hat{x}_{(k)}$$

and on the covariance of the error of the estimates of the $P(k)$ system. Recursively, the values are updated, starting a new pet.

3.2 THE SPEED ESTIMATION USING EKF

Based on equations (15) to (19), the estimation of the MI velocity will be obtained using the expressions given below.

3.2.1 PREDICTION STEP

$$F_{(k)} = \frac{\partial}{\partial x}(Ax + Bu) \Big|_{x=\hat{x}_{(k-1)}} \quad (23)$$

that is, $F(k)$ is given by:

$$\begin{vmatrix} 1 - a_1 T_s & 0 & a_2 T_s & a_3 \hat{\omega}_r T_s & a_3 \hat{\phi}_{\beta_r} T_s \\ 0 & 1 - a_1 T_s & -a_3 \hat{\omega}_r T_s & a_2 T_s & -a_3 \hat{\phi}_{\alpha_r} T_s \\ a_4 T_s & 0 & -a_5 T_s & -\frac{n_p}{2} \hat{\omega}_r T_s & \hat{\phi}_{\beta_r} T_s \\ 0 & a_4 T_s & -\frac{n_p}{2} \hat{\omega}_r T_s & -a_5 T_s & a_3 \hat{\phi}_{\alpha_r} T_s \\ 0 & 0 & 0 & 0 & 1 \end{vmatrix} \quad (24)$$

3.2.2 CORRECTION STEP

$$H_d = \left. \frac{\partial C_d x}{\partial x} \right|_{x=x_{(k)}} = \begin{vmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{vmatrix} \quad (25)$$

From equations (17) and (18), the vector of estimated states

$$\hat{x}_{(k)}$$

and the covariances of estimation errors

$$\hat{P}_{(k)}$$

are corrected

$$\hat{x}_{(k)} = \hat{x}_{(k)}^- + K_{(k)} [z_{(k)} - H_{d(k)} \hat{x}_{(k)}^-] \quad (26)$$

At each measurement, the filter stores the matrices calculated in the previous step and returns to the beginning of the process in order to estimate the next

$$P_{(k)} = (I - K_{(k)} H_{d(k)}) P_{(k)}^- \quad (27)$$

and

$$\hat{P}_{(k+1)}$$

values and until EKF convergence is obtained.

3.3 OFF-LINE TUNING OF COVARIANCE MATRICES P and Q

The performance of the estimation is directly affected by the values chosen for the initialization of the Q, P and R covariance matrices, most often based on trial and error (RAYYAM *et al.*, 2018). Several studies have been developed to meet the harmony of these matrices.

In Zerdali and Barut (2017), the authors use a differential evolution algorithm (DEA) and a multi-objective DEA (MODEA) associated with different adequacy functions.

Yin *et al.* (2017) uses a sequence of multiple EKF filters (MM-EKF), where different weights are assigned to each term of the set enabling the introduction of new information and, consequently, performance improvement and reduction of estimates error.

In Wallscheid *et al.* (2018), a joint project is presented to observe the speed, flow, torque and estimation of the electrical parameters of the IM by means of a UKF. Although the UKF showed a better linear approximation compared to the EKF, the UKF estimator showed greater sensitivity to the noise of the online measurements, leading to a lower accuracy of the speed and torque estimates.

The method proposed here for off-line tuning for the initialization of the Q and P covariance matrices was developed from Estevam *et al.* (2014), where the absence of mechanical equations in the EKF model hinders the convergence of speed estimation, usually obtained through the filter gain adjustment. The terms of the diagonal matrix $P_{5 \times 5}$, which are correlated with higher expectation of uncertainties in the estimation, and the terms of the diagonal matrix $Q_{5 \times 5}$ that are correlated with greater predisposition to noise of the estimation process should assume high values, respectively for p_{55} and q_{55} , and lower values for q_{11} and q_{33} . The influences of P and Q on the estimation of velocity were analyzed with the control system operating in open mesh, that is, the EKF is not influencing the logic of the PI controllers of the vector control.

The offline tuning of the matrices of covariance of estimation uncertainties, system noise and measurement P, Q and R, is based on knowledge about the dynamic behavior of the induction motor and the application of statistical tools through the expected value, mean,

Gaussian probability distribution, variance and covariance. In this way, the values for the terms of the matrices are obtained.

4. SIMULATION RESULTS

The simulations were performed in MatLab®, considering the control in open mesh and in closed mesh using the values estimated by EKF.

The data used in the simulation were from the engine model 5K33GN2 - Marathon (Regal Beloit Corporations), available in www.regalbeloit.com/Products/Catalog. These characteristics were adopted in the simulations, aiming at the stage of practical implementation.

The speed profile included references at 90 rpm, 900 rpm and 1740 rpm, equivalent to 5%, 50% and 100% of the nominal speed of the induction motor, with frequency of skewing of IGBTs at 4kHz, under empty operating conditions and with load.

The values, estimated from the EKF algorithm, for the conjugate and electromagnetic flow, speed and mechanical position of the rotor were applied in place of the variables necessary for vector control.

The expressions (28), (29) and (30) indicate the tuned matrices for the simulation results.

$$P = \begin{bmatrix} 0.5 & 0 & 0 & 0 & 0 \\ 0 & 0.5 & 0 & 0 & 0 \\ 0 & 0 & 0.5 & 0 & 0 \\ 0 & 0 & 0 & 0.5 & 0 \\ 0 & 0 & 0 & 0 & 50000 \end{bmatrix} \quad (28)$$

Where:

$$Q = \begin{bmatrix} 0.000024 & 0 & 0 & 0 & 0 \\ 0 & 0.000024 & 0 & 0 & 0 \\ 0 & 0 & 0.000024 & 0 & 0 \\ 0 & 0 & 0 & 0.00024 & 0 \\ 0 & 0 & 0 & 0 & 240000 \end{bmatrix} \quad (29)$$

$$R = \begin{bmatrix} 2.4 & 0 \\ 0 & 2.4 \end{bmatrix} \quad (30)$$

The graph shown in Figure 3 attests to EKF convergence in estimation accuracy, whether at speeds close to zero, intermediate speeds, or nominal velocity. The estimation presents values close to the reference speed and the speed calculated by the mathematical model of the induction motor.

Figure 3. Variable speed (90rpm, 900rpm and 1740 rpm).

Source: The author himself

The graph in Figure 4 shows the dynamic response of the EKF to the mechanical position of the rotor, with convergence in the estimation for values close to the mechanical position calculated by the mathematical model of the induction motor.

Figure 4. Position in radians in time $(-\pi, 0, \pi)$.

An Extended Kalman Filter, with pre-adjusted covariance matrices, applied to the sensorless speed control of three-phase induction motors

Source: The author himself

Taking the measurement of the position in radians in time, with trajectory ranging from π to π , the EKF estimator demonstrates precision and convergence at lower speeds, for example 90 rpm, as well as at average speeds. Deviations from the instant 25 seconds in Figure 3, where the speed is switched to 1740 rpm. In this case, the deviations are due to the logic of updating the estimates, which are directly linked to the P matrix of covariance of estimation errors. The uncertainties of the estimates present evidence due to the iterations of the values treated by the prediction phase and, later, correction of estimates.

The graph shown in Figure 5 outlines the variation in the mechanical position of the rotor in degrees.

Figure 5. Position in degrees $0^\circ \dots 360^\circ$ ranging with 90rpm, 900rpm, and 1740 rpm speed.

An Extended Kalman Filter, with pre-adjusted covariance matrices, applied to the sensorless speed control of three-phase induction motors

Source: The author himself

$$\frac{d\theta_{mec}}{dt} = \omega_r \quad (31)$$

Where:

However, the presence of oscillations around the reference values is observed. These oscillations can be minimized by adjusting and tuning the EKF, basically on the q, r, p and k covariance matrices of the EKF. The largest oscillations stand out in operation at low and transient speeds.

When the P matrix of state estimator error covariance approaches zero, the Gain K matrix

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acts less intensely to minimize the discrepancy between the prediction values and the measures taken on the machine model.

If higher values are adopted for the elements of the noise covariance matrix (Q) there is a higher degree of uncertainty regarding the estimates of the system states, implying the increase of the K -gain matrix and an increase in the convergence speed of the estimation.

The increase in the values of the elements of the covariance matrix of the measurement noises of currents and voltages, R , implies the decrease of the matrix of the K gain, which acts in the reduction of the response speed of the EKF.

5. Conclusions

The simulated results indicate the viability of the estimator based on the indications of its ability to respond to the variations in speed imposed on the control system, as well as different load conditions imposed on the engine.

Induction motor operating conditions with different loads, up to 400N, or approximately 40kg of weight, were simulated. The charging values are based on the capacity of the engine mechanical torque, according to the manufacturer's datasheet, being 1.1 N.m with a rated speed of 1725 rpm.

The EKF estimation presents convergence with the reference values and calculated values, according to the operation dynamics imposed on each load condition.

In possession of the results presented, it is expected to implement the solution in a hardware for digital control of engines using the digital signal processor of the Manufacturer Texas Instrument, model TMDSHVMTRPFCKIT with control plate F28035 and a three-phase asynchronous induction motor of squirrel cage type, model 5K33GN2, marathon manufacturer (*Regal Beloit Corporations*), available at PPGEE - PUCMINAS.

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Submitted: August, 2020.

Approved: September, 2020.